A QUANTITATIVE, MODEL-DRIVEN APPROACH TO TECHNOLOGY SELECTION AND DEVELOPMENT THROUGH EPISTEMIC UNCERTAINTY REDUCTION

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A QUANTITATIVE, MODEL-DRIVEN APPROACH TO TECHNOLOGY SELECTION AND DEVELOPMENT THROUGH EPISTEMIC UNCERTAINTY REDUCTION

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To my parents, thank you for everything.

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LIST OF SYMBOLS OR ABBREVIATIONS

AD^2 Advancement Degree of Difficulty.

ANN Artificial Neural Network.

ANOPP Aircraft Noise Prediction Program.

ANOVA Analysis of variance.

CAEP Committee on Aviation and Environmental Protection.

CAEP6 Committee on Aviation and Environmental Protection Tier 6 NOx rule.

CDF Cummulative Distribution Function.

CMPGEN Compressor Map Generator.

CRM Continuous Risk Management.

DOD Department of Defense.

DOE Design of Experiment.

EDS Environmental Design Space.

EINOx NOx emissions index.

ERA Environmentall Responsible Aviation.

FLOPS Flight Optimization System.

GAO Government Accountability Office.

GSA Global sensitivity analysis.

HPC High pressure compressor.

HPT High pressure turbine.

HWB Hybrid wing body aircraft.

ICAO Internatioal Civil Aviation Organization.

IMM Integration Maturity Metric.

IPPD Integrated Product/Process Development.

IRL Integration Readiness Level.

ITAM Integrated Technology Analysis Method.

ITI Integrated Technology Index.

LPC Low pressure compressor.

LPT Low pressure turbine.

LSA Large single aisle, tube and wing aircraft.

LTA Large twin aisle, tube and wing aircraft.

LTO NOx Landing and takeoff NOx emissions.

MCS Monte Carlo Simulation.

MRL Manufacturing Readiness Level.

NASA National Aeronautics and Space Administration.

NPSS Numerical Propulsion System Simulation.

OEW Operating empty weight.

OPR Overall Pressure Ratio.

P3T3 Pressure and Temperature Correlations.

PDF Probability Density Function.

POS Probability of Success.

PRA Probabilistic Risk Analysis.

QuantUM^3 Quantitative Uncertainty Modeling, Management, and Mitigation methodology.

R& D^3 Research and Development Degree of Difficulty.

RSE Response Surface Equation.

SA Sensitivity analysis.

SME Subject Matter Expert.

S/N Signal to noise ratio.

SRL System Readiness Level.

TCE Tail Conditional Expectation.

TCM Technology Compatability Matrix.

TDPM Technology Development Planning and Management.

TIES Technology Identification, Evaluation, and Selection.

TIF Technology Impact Forecasting.

TIM Technology Impact Matrix.

TOGW Takeoff gross weight.

TPM Technical Performance Measures.

TRA Technology Readiness Assessment.

TRL Technology Readiness Level.

TSFC Thrust specific fuel consumption.

TVN Technology Need Value.

WATE Weight Analysis of Turbine Engines.

WPV Worst possible value.

SUMMARY

The objective of this research was to develop a methodology that aids risk-informed decision-making throughout a technology development program. Specifically, the methodology is aimed towards quantifying and communicating technology readiness and technology performance and the impact they have on their intended aircraft system. The performance impact a technology will have is the result of a forecast when the technology is not fully developed. Therefore, there will be uncertainty surrounding its performance impact that in turn causes uncertainty to surround the anticipated system level performance. As the readiness of a technology increases, the uncertainty is expected to decrease. Identification of what is causing the uncertainty to exist aids experiment planning, where the objective of the experiments is to burn down the uncertainty and pinpoint the exact performance of the technology while simultaneously increasing its TRL. Since the uncertainty under consideration is assumed to be reducible, it is characterized as epistemic uncertainty.

The method created in this research encompasses four main phases of technology development: Strategic Planning, Technology Selection, Technology Experimentation, and Technology Transition Readiness. It was recognized that a methodology encompassing all of these development phases is in theory a series of prioritizations, where appropriate alternatives must be identified, appropriate metrics must be selected, and analysis procedures must be outlined and required tools must be gathered to enable the calculation of the metric values for each alternative. Therefore, the methodology was created by enumerating the key decisions, identifying potential metrics for readiness risk and performance risk, and outlining the required analysis procedures. The integration of the resulting processes tested and selected for each

key decision form the overall methodology.

In Strategic Planning, the topics of system architecture selection, performance goal setting, and the identification of key low and mid-level impacts driving the objective metrics are addressed. Architectures are assessed using a technology forecasting procedure paired with uncertainty quantification techniques to create probabilistic performance assessments of each architecture under consideration. Key impacts that drive the performance objective metrics are found through a series of sensitivity analyses. Finally, impact scenarios are identified by filtering the probabilistic results based on set performance goals. The impact scenarios provide required deltas in the impact variables in order to ensure the goals are met.

In Technology Selection, the objective is to identify viable technology portfolios from a provided set of technologies, analyze them, and then select the final portfolio. It is suggested that technology portfolios can be formulated through a series of performance-based prioritizations of the technologies on an individual basis. Once technology portfolios are formulated, they are analyzed to determine their readiness risk and performance risk. Several measures of likelihood and consequence were identified for both readiness and performance, and all possible combinations were tested. For readiness risk, aggregate TRL measures were enabled through the use of a cardinal TRL scale. These measures were paired with measures of difficulty to communicate readiness risk. For performance risk, the S/N metric was identified as a way to capture both the expected performance and variability. It was utilized along with probability of success to represent performance likelihood. Performance consequence was captured through the use of two different metrics, the tail conditional expectation and the worst possible value. The results of the portfolio assessments were then input into a multi-attribute decision making technique to demonstrate how the information could be used to facilitate technology portfolio down-selection.

For Technology Experimentation, a method was formulated that combines a new readiness assessment method with uncertainty quantification results to identify experiment goals for prioritized technologies. The readiness assessment method formulated within this research utilizes morphological analysis and the existing TRL definitions in the literature to identify the type of experimentation that is expected at each TRL level. The technologies are then prioritized for experimentation based upon their individual readiness risk and performance risk. Once a technology is selected for experimentation, further uncertainty analysis is conducted to identify the objective of the experiment. A combination of this information with the readiness information provides the answers to: What is being tested? Where is it being tested? What is the purpose of the test?

The last phase of development, Technology Transition Assessment, involves determining whether a technology is ready for transition into the system and whether it is still worth pursuing. It is demonstrated in this research that repeating readiness and performance risk analyses throughout development is important with respect to tracking the progress of the technologies on an individual basis as well as at the portfolio level. Furthermore, identification of ideal and non-ideal risk trends aids risk mitigation planning efforts.

Development and testing of this methodology was facilitated through the use of an environmentally-focused case study. Altogether, this method fills an identified gap in the literature, which is a synthesis of subjective, qualitative readiness assessments and quantitative, probabilistic performance assessments. Providing information from both of these assessment types creates the clearest picture of the overall maturity of a technology and what it is expected to contribute to the intended system. This will enable risk-informed decisions on what technologies to pursue, and what technologies to continue pursuing throughout the program life cycle. Furthermore, it provides a way to not only account for epistemic technology uncertainty, but plan experimentation to decrease the amount that exists in selected technology portfolio.

CHAPTER I

INTRODUCTION

The National Aeronautics and Space Administration (NASA) Aeronautics Research Mission Directorate (ARMD) has set forth aggressive environmental and performance goals that require the integration of new, advanced technologies into next generation aircraft concepts to bridge the gap between current and required capabilities. A large number of technologies exist that can be pursued, and only a small subset may practically be selected to reach the chosen objectives for the allocated budget. Additionally, the appropriate numerical and physical experimentation must be identified to further develop the selected technologies to the desired level of maturity.

Making risk-informed technology development decisions is important because stakeholders do not want to invest in technologies that will not eventually pay dividends. Therefore, the right decisions need to be made without taking unnecessary risks or wasting resources. This leads to a series of questions that a program needs to address: *What technologies and experiments should I be pursuing? How confident am I in this? What is the consequence if I am wrong?*

Furthermore, technologies are eventually integrated into the development process of the intended vehicle system. It is imperative that technologies reach a certain level of maturity and their performance is test-proven before they are integrated into system development or they can greatly impact the overall risk of the entire system development. Studies conducted by the Government Accountability Office (GAO) on Department of Defense (DOD) acquisition discovered programs that begin their development process with mature technologies are less susceptible to schedule and cost overruns and are more likely to meet their performance objectives[31, 32, 33, 35, 98, 112]. For example, a GAO study conducted in 2009 assessed all of the DOD systems under development in 2008 for cost and schedule overruns. Of the 48 programs in the DOD portfolio that year, 36 reported data on the maturity levels of their critical technologies. Of these 36 systems, only four reported using mature technologies that had been previously demonstrated in a relevant environment. These four programs experienced 30 percent less overrun in research and development costs compared to the other 32 systems.

Making decisions with regards to developing entities can be difficult because new technologies can introduce phenomena that have not been seen or studied before. Pairing these technologies with new vehicle system concepts adds to the complexity. Characterization of new phenomena cannot be fully completed until it is thoroughly tested. However, testing of full scale systems with all technologies integrated is not commonly feasible until the late stages of development and, therefore, existing performance assessments are the result of forecasts. Uncertainty in the forecasts exists because the impacts of the technologies on the system, and the system design itself, are not exactly known. However, the acknowledgment of the existence of uncertainty does not necessarily mean it is accounted for. Traditionally, the disciplines of science and engineering have strongly tended to emphasize what is known, or thought to be known, instead of what is uncertain[77].

In the past, the methods used to aid risk-informed decisions were based on deterministic, technology-level performance assessments and qualitative measures of readiness, such as the existing Technology Readiness Level(TRL) system. The TRL system provides a tool for communication across disciplines; however it provides limited information on the risk a technology introduces to a system, and any information it does provide is subjective and qualitative. The ability to characterize the technology impact uncertainty and pinpoint how it is driving the system performance would provide decision makers with quantitative, supplemental information. Previously, this type of information has not been available due to limited resources and methods. However, new assessment methods and enabling tools exist that can provide integrated, automated system performance assessments.

Advancements in the field of computer science over the past 50 years have led to the use of computer models and simulations for engineering problem solving[93]. The terms 'model' and 'simulation' have various meanings in different disciplines. Conway et al. defines simulation as a type of experimental investigation[23], whereas Burdick and Naylor define it as a numerical technique for conducting experiments on certain types of mathematical and logical models describing the behavior of a system on a digital computer over extended periods of real time[20]. Fox et al. states the term 'modeling and simulation refers to the use of computer models to emulate a system to provide insight into its operation without actually operating it'[30].

System modeling provides many benefits, including the ability to conduct a large number of assessments over a short period of time, a safer testing alternative for live experiments with potential consequences, and identification of system shortcomings before live tests are conducted[30]. In design, modeling and simulation is used to study systems that are otherwise impossible, infeasible, inconvenient, and/or not viable to study[23].The design of complex systems requires lengthy and expensive testing programs, and often it is too expensive to physically conduct all experiments of interest; therefore, computer based modeling and simulation provide a means to conduct further assessments for less cost[89]. This capability is attractive to system designers and project managers because more available information enables better informed decisions[77]. The realization and implementation of this benefit has caused terms such as virtual prototyping and virtual testing to emerge in the engineering community to define how computer-based modeling environments can be used in testing and evaluation of new systems or new system components[77].

Modeling and simulation can be utilized in all phases of design or development. Low-fidelity, generic, high-level modeling is usually utilized during the conceptual design phase to evaluate concepts and alternatives. Alternatively, physics-based, detailed models are utilized in support of testing and evaluation activities[30]. Determination of adequate model fidelity and complexity depends on the objective of the analysis at the given phase of development. Selection of the proper model(s) is sometimes an iterative process; simplified models may be chosen early in development to identify and characterize dominant physical processes, and then more complex models are built or selected to produce more detailed analyses for later design stages[105].

Based on this information, key observations were made:

- Developing technologies are surrounded by uncertainty that hinders decision making
- It is important to make risk-informed technology development decisions to prevent risk propagation to system development
- The state of the art of modeling and simulation has advanced and its new capabilities can be leveraged in the fields of science and engineering

Based upon these observations, it is felt that new, quantitative methods have the potential to revolutionize the way technology development decisions are made. Therefore, the top level goal of this research is to investigate methods that provide quantitative information to aid risk-informed technology development decisions. It has been established that when a large amount of uncertainty is present in a system assessment it is difficult for decision makers to make these important development decisions. Risk is a function of uncertainty, which means the uncertainty surrounding the performance of a system due to a low-maturity technology contributes to the system risk. Therefore, reducing uncertainty can be seen as a surrogate for reducing risk because it increases the confidence in the beneficial or detrimental effect of a technology. Information about the component of system risk that is introduced by a technology can help guide decisions made during the development process. Technology development decisions should be risk-informed to ensure that risk decreases as the development program progresses.

Information from quantitative, probabilistic system performance assessments has not previously been synthesized with qualitative readiness assessments. However, a combination of all of this information has the potential to provide the clearest picture of the development status of a single technology, group of technologies, or system, as well as characterization of its predicted performance attributes. This synthesis of information could aid risk-informed technology selection and experiment planning decisions throughout technology and system development. The type of information required to make risk-informed decisions at all stages of development, and the processes that should be followed to ensure the highest quality information is obtained, has not been previously established and is an identified gap in the literature.

This research aims to fill this gap by identifying and developing processes that enable risk-informed technology development decisions. The foundation of the processes will be centered around physics-based system assessments and uncertainty quantification methods. Therefore, the main research objective is as follows:

Research Objective: Formulate a model-driven process that utilizes uncertainty quantification methods to provide information that enables risk-informed technology development decisions.

- The methodology will encompass all relevant phases of development and address the corresponding key decisions
- Quantitative methods and subject matter expert-driven methods will be investigated, and their resulting information will be integrated to provide a holistic view of readiness

Overall, this research aims to establish the necessary methods and subsequent information required to facilitate risk-informed decisions at each step of the development process. After the declaration of the formal research question, further definition of the research scope was required. Therefore, three motivating questions were identified. These motivating questions are as follows:

Motivating Question 1: What are the key phases of technology development that need to be addressed in this research and the key decisions associated with each phase?

Motivating Question 2: What definition of risk is appropriate for this research?

Motivating Question 3: What types of risk should be quantified to enable risk-informed technology development decisions?

The remainder of this chapter will address research areas relevant to the motivating questions. First, the topics of technology development and system development are presented to provide a clear delineation of the responsibilities and objectives of each. This research will solely focus on technology development decisions, so the different phases of development and key decisions need to be identified and enumerated. Next, the topic of risk is presented to enumerate the types of risk that may be relevant to technology development and existing assessment and management procedures.

1.1 System and Technology Development Process

A technology undergoes its own development process and is eventually either transitioned into a system's development process or shelved for many years[31, 32, 34]. The goal of system development is to develop and deliver a system that meets the stated objectives. A system contains multiple technologies, each of which provides a capability to the system. Therefore, if new, non-existent capabilities are desired, then new technologies will need to be developed.

Technologies may be developed in-house by the same organization developing the system, developed by a different division or group within the same organization, or developed by an outside organization. This means there is potential for one entity to be responsible for system development and a separate entity to be responsible for the development of a supporting (or potentially supporting) technology. Therefore, programs generally distinguish technology development from system development.

The following definitions will be used to distinguish the goals of technology development from system development:

- **Technology Development:** The process of testing and analysis that progressively increases the readiness of a technology until it is demonstrated in a relevant environment [61]

- **System Development:** System development is the process of testing and analysis that results in delivery of a system

Many successful development programs, whether they be technology or system, have moved towards a gated approach that was formalized by Cooper in the 1980s[33]. Cooper formalized the gated process because he felt that there existed a gap between research discoveries about causes of failed development programs and new recommended practices for remedying failed developments[24]. He found there was a strong correlation between the quality of execution of a detailed development process and the success or failure of a product being developed, so he proposed that programs should establish key evaluation points throughout the development process to fill this gap. The decision points were to serve as "gates", and at these gates, decision makers were to determine the fate of the program. Specifically, he suggests that decision makers would decide to "GO" (continue with the program), "KILL" (end the program), or "HOLD"(pause the program).

Leading companies now use gated management review processes that stem from Cooper's work to ensure they are tracking a developing entity's relevancy, feasibility, and readiness throughout he entire development process. For example, Boeing utilizes a four-gate process, 3M utilizes a three-gate process, and Motorola utilizes a five-gate process[33]. Gates separate different phases of development, and each phase has a specific objective. When the work in a phase is completed, the key decision at the gate must be made in order to move to the next phase of development[67]. Generically speaking, Figure 1 displays the distinguished difference between system development and technology development in a two-phase product development process.

Figure 1: Two-Gate Product Development Process

The generic two-phase, one-gate development process resembles the process that used to be the status quo within the DOD. The DOD's development process also included a pre-Technology Development phase called Concept Refinement. During Concept Refinement an analysis of alternatives and down-selection for the system concept was conducted before Technology Development began. During Technology Development technologies were matured until they were demonstrated in a relevant environment, system requirements were documented, and a system acquisition strategy was produced. At the end of Technology Development, the System Development (or Program) started. Shortcomings in this three-phase approach caused the DOD to reform their process into a five-phase approach that includes the entire life cycle of a product. Figure 2 displays the current acquisition process utilized by the DOD.

A, B, and C correspond to major program milestones, which are synonymous to gates.

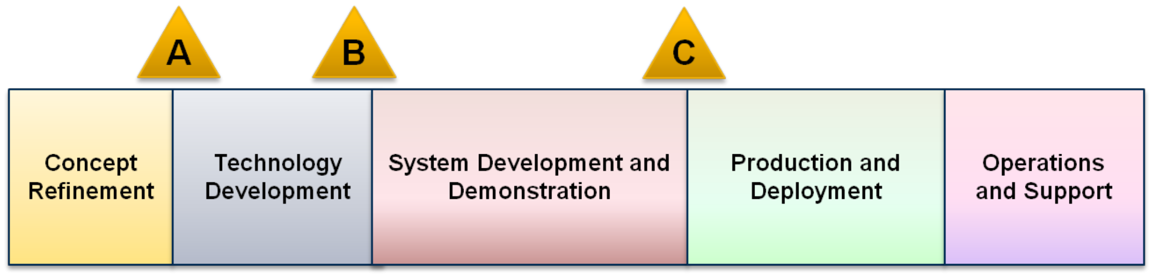

Figure 2: Department of Defense System Acquisition Process

It has been previously stated that studies have shown the success of DOD programs depends heavily on the status of technologies when they are transitioned into programs for System Development. Furthermore, there has been debate on whether the transition phase is the responsibility of the entity conducting Technology Development or System Development. If the entity doing both technology and system development is the same, then distinction of responsibility may not be important; however, it has been recognized that the processes are sometimes conducted by separate entities. Figure 3 and Figure 4 show sample gated processes where the responsibility of transition varies between Technology Development and System Development.

Figure 3: Transition as Part of Technology Development

Figure 4: Transition as Part of System Development

GAO assessed how leading companies handle Technology Development and System Development, and they determined there were sets of activities, or sub-phases, relevant to each. Their study concluded that technology transition should be considered a sub-phase of Technology Development, but requirements of the sub-phase should be defined with respect to what is needed to begin System Development successfully[33]. After completing their assessment of leading development strategies, the GAO recommended a five-phase development process that includes Strategic Planning, three sub-phases of Technology Development, and System Development. The objective of the first phase, Strategic Planning, is to conduct initial concept formulation as well as concept refinement. The three sub-phases of Technology Development are defined as Explore, Develop, and Transition. The objective of Explore is to down-select the technologies to be developed, the objective of Develop is to select and implement the development plans for the selected technologies, and the objective of Transition is to transition the ready technologies into System Development. Figure 5 shows what this generic five-gate process would look like.

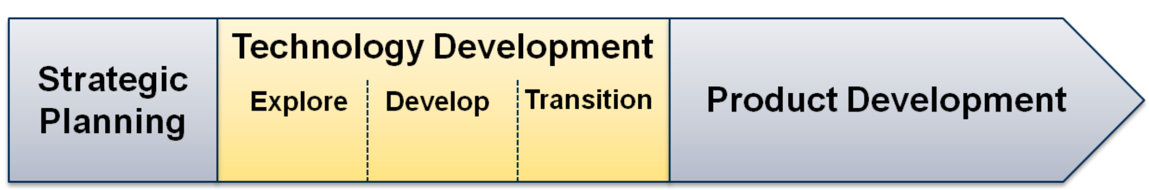

Figure 5: Five-Gate Standard Development Process

1.1.1 Motivating Research Question 1

It was established that gated approaches are followed for development programs. Gates are milestones where key decisions must be made and serve as a separation between development phases. Each phase has a main objective, which usually is focused on gathering the information needed to support the key decision making. When a gated approach is utilized, technology development can be thought of as a set of decisions that will lead to a set of technologies ready for transition into system development.

The GAO synthesized best practices from existing development programs and stated transition is more successful when it is done by the entity in charge of Technology Development. Additionally, they defined a development process that has three main phases(Strategic Planning, Technology Development, and System Development), and three sub-phases for Technology Development. Based on these observations, a process that wishes to track risk throughout technology development should include aspects of objective setting, technology selection, technology maturation, and technology transition readiness assessment. Therefore, this research will be developed around the phases and sub-phases of the development process defined in Figure 6. Other aspects of development outside of these defined phases (i.e. production and deployment, operations and support) will not be included in the scope of this research.

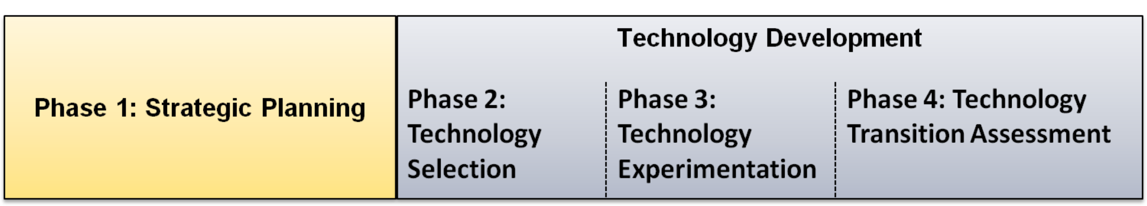

Figure 6: Development Phases for Thesis Formulation

1.2 Risk Definitions

The term risk is often used in many contexts. There are several available definitions in the literature, and the way risk is defined affects the way it is measured as well as the way it is managed. Frank Knight provided a fundamental definition of risk in 1921. This classical definition of risk is stated as: "The essential fact is that 'risk' means...a quantity susceptible of measurement... It will appear that a measurable uncertainty, or 'risk' proper... is so far different from an immeasurable one that it is not in effect an uncertainty at all. We ... accordingly restrict the term 'uncertainty' to cases of the non-quantitative type. e.g. If it is measurable, it's risk. If it is not measurable, its uncertainty." [60] This definition makes it evident that the concepts of uncertainty and risk have been associated with each other from the very beginning.

The modern, or Hubbardian, definition of risk is "A state of uncertainty where some of the possibilities involve a loss, catastrophe, or other undesirable outcome". Again the concepts of risk and uncertainty are mentioned together; additionally, this definition introduces the notion of a consequence. This modern definition, one that includes a state of uncertainty and potential consequence(s), has sparked further development of the definition of risk as well as quantitative risk measures.

NASA risk management followed the modern risk definition and separated risk into two components: the likelihood of failing to achieve a particular outcome and the consequence of failing to achieve that outcome. To go with this definition, they defined the risk measure as the measure of the potential inability to achieve a goal or target with defined safety, cost, schedule, and technical constraints.[109] This risk measure only captures the 'consequence' portion of the risk definition.

An alternative risk measure found in the literature is the probability, or likelihood value, of the event multiplied by the associated consequence of the event. The consequence measure is synonymous to the risk measure from above, which is the probability of not meeting a defined goal or target. This measure is quantitative and represents both aspects of the risk definition, uncertainty and consequence, but has received criticism. Kaplan points out that this risk measure definition could provide misleading risk assessment results because multiplication of the likelihood and consequence could equate a low-probability high-damage scenario and a high-probability low-damage scenario as the same thing. [50]

Recently, the standard definition for risk follows the "risk triplet" approach. The risk triplet is defined as [9, 50, 105]:

1. What are the scenarios? (What can go wrong?)

2. What are the likelihoods of the scenarios?

3. What are the consequences of the scenarios?

This definition incorporates uncertainty and consequence. However, it keeps the different risk scenarios separate and does not attempt to shrink them into a one dimensional measure. Unlike multiplying likelihood and consequence, defining risk using the triplet inhibits risk management because it distinguishes high-probability, low-consequence outcomes from low-probability, high-consequence outcomes [9, 50]. This definition points the way to proactive risk management controls, and is the current standard used in many industries and agencies, including NASA [9].

1.2.1 Motivating Research Question 2

Multiple definitions of risk were provided. It is observed that most definitions included the concepts of likelihood and consequence. Some risk measures combined the two concepts, such as by multiplying or adding them, to formulate a single metric risk definition. However, these measures have the potential to provide misleading risk information because high likelihood, low consequence risks can be confused with low likelihood, high consequence risks.

Due to this concern, the current standard definition of risk is the risk triplet. The risk triplet keeps the measure of likelihood separate from the measure of consequence for each individual risk scenario considered. This definition is amicable to this thesis' research objective because it provides a place for uncertainty quantification results and different scenarios, which could be different technologies or technology combinations. Scenarios are important when deciding among different alternatives because you want to create a situation where comparisons are being made for similar entities. Therefore, the definition of risk for the remainder of this research will be the risk triplet.

1.3 Risk Classification

There are many different risk classifications that exist. The classification of a risk depends on the nature of the consequence of the risk scenario. For example, if a scenario has a potential negative impact on the cost of a program, it is considered a cost risk for that program. In the program management world, cost risk and schedule risk are common terms. Their definitions are fairly straightforward. Cost risk implies a potential to overextend the defined budget constraints, whereas schedule risk implies a program has the potential for defined tasks to be incomplete at the planned end date.

When new systems are being developed they usually have specific performance objectives they aim to meet. As previously mentioned, the insertion or planned insertion of immature technologies could add performance uncertainty to the program because the exact performance of the technologies is not known. The performance uncertainty and the potential shortfalls with respect to meeting performance requirements is the performance, or technical, risk [105, 87].

While performance, cost, and schedule risk are the most common risk classifications in system development, there are also others. Examples of such are investment risk, political risk, market risk, reputation risk, and competition risk. Again, the classification of risks depends on the nature of the consequence. It is also important to note that some risks are not always identified, or classified, because that type of risk is not being sought out. NASA's risk management guide categorizes different risk classifications into two groups, program risks and enterprise risks. At the program level NASA considers performance, schedule, and cost. At the enterprise level NASA considers time, market, and competition. This is just one example of how the type of risk categories considered changes as the goal or objectives change.

1.3.1 Motivating Research Question 3

Various types of risk were identified, such as cost, schedule, performance, competition, market, etc. It is important that all risks relevant to technology development are quantified, but information about all types of potential risk are not required to enable risk-informed decisions. Cost and schedule considerations are important to any type of program, including a technology development program. Therefore, cost and schedule risks would be important to track and consider during decision making. However, this research aim to focus on the technical aspects of technology development.

The GAO identified that the leading causes for system risks are under-developed technologies that haven't been properly demonstrated and have existing performance uncertainty. Both of these, technology readiness and performance uncertainty, are technical risk aspects that should be considered throughout technology development. Some argue that tracking performance risk or performance uncertainty implicitly provides you with a measure of readiness, and vice versa. However, no standard for translating between readiness and performance uncertainty has been established. In addition, it is thought that an explicit measure of readiness paired with a probabilistic performance risk analysis will not hinder decision makers and will provide more potentially valuable information. Therefore, this thesis will focus on providing relevant information about readiness risk and performance risk for the the previously enumerated key decisions of each development phase.

The definitions of performance risk and readiness risk that will be used in this thesis are as follows:

Readiness Risk: the likelihood a technology is ready, or not ready, for transition into system development by the provided time within the given resource constraints and the potential consequences of it not being ready.

Performance Risk: the uncertainty of a technology's performance impact and the potential shortfalls with respect to meeting performance objectives.

1.4 Research Outline

The motivation and need for this research has been identified and led to the definition of the formal research objective. Furthermore, addressing the three motivation research questions provided a more concrete definition of the scope of this research. The following chapters will provide further problem formulation (Chapter Two) and the definition of the proposed research questions and corresponding hypotheses that will define the proposed methodology (Chapter Three). Relevant background information on the current state of the art and supporting processes that will be utilized will be provided throughout the problem formulation and methodology definition. Next, an experimental plan was formulated to test the hypotheses and the resulting overall methodology and is presented along with the motivating case study (Chapter Four). The results of the experiments that are used to finalize the methodology will be provided in Chapter Five and Chapter Six. Chapter Seven will synthesize the final methodology and provide a final implementation to demonstrate the benefits the methodology provides. The dissertation concludes in Chapter Eight with a discussion of the overall research findings and the proposed future work.

CHAPTER II

PROBLEM FORMULATION AND BENCHMARKING

Chapter One defined the phases of technology development that will be addressed through this research as *Strategic Planning*, *Technology Selection*, *Technology Experimentation*, and *Technology Transition Readiness Assessment*. Each development phase has key decisions that must be made before progression to the next phase is allowed. The first step to forming the methodology to be developed was to identify the decisions that must be made within each development phase. Table 1 displays the development phases and corresponding key questions that will be addressed in this thesis.

Table 1: Development Phases and Key Questions

Phase	Key Questions
Phase 1: Strategic Planning	What is the system architecture?
	What are the objectives?
	What are the important metrics for the given objectives?
	What capabilities/impacts are needed to meet the given objectives?
Phase 2: Technology Selection	What technologies should be pursued?
Phase 3: Technology Experimentation	What development activities should be performed?
Phase 4: Technology Transition Readiness Assessment	What technologies will be transitioned?

It is recognized that making any of these technology development decisions, or any decision in general, requires the information provided in Figure 7: alternatives, metrics, means for analysis, and means for prioritization. Therefore, it is recognized that the development phases can be seen as a series of prioritizations. In Phase One, the objective is to prioritize the different architectures and the capabilities driving the performance objectives. In Phase Two, the objective is to prioritize technologies to enable technology down-selection. In Phase Three, the objective is to prioritize experimental efforts to facilitate epistemic uncertainty reduction and technology maturation. Finally, the final prioritization in Phase Four is again for the technologies to determine which are ready for transition into vehicle system development.

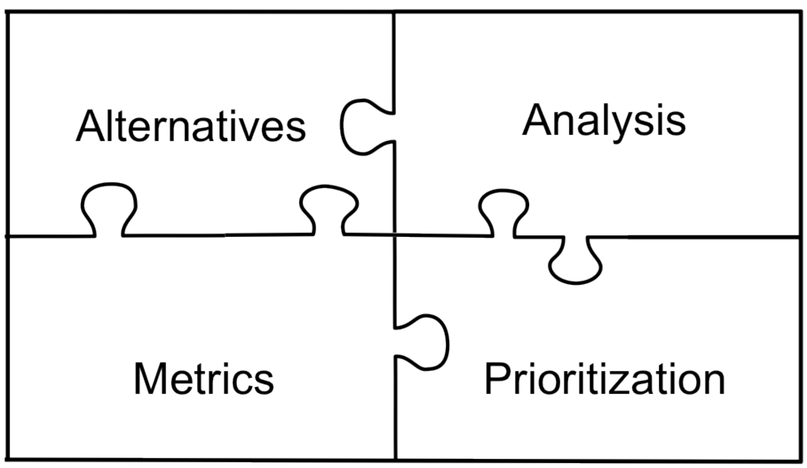

Figure 7: Information required for decision-making.

The required information provided in Figure 7 and the process of prioritization is recognized as a sequential decision making process. Furthermore, the goal of this research is not to determine the best existing decision making process or create a new decision making process; rather, the goal is to determine the correct type of information to aid these decisions and then determine the process that should be followed to create that information. Background research into existing decision support frameworks led to the identification of a generic top-down decision making process developed for the Integrated Product/Process Development (IPPD) methodology[69].

The process is shown in Figure 8 and has six main steps: establish the need, define the problem, establish the value, generate alternatives, evaluate alternatives, make a decision.

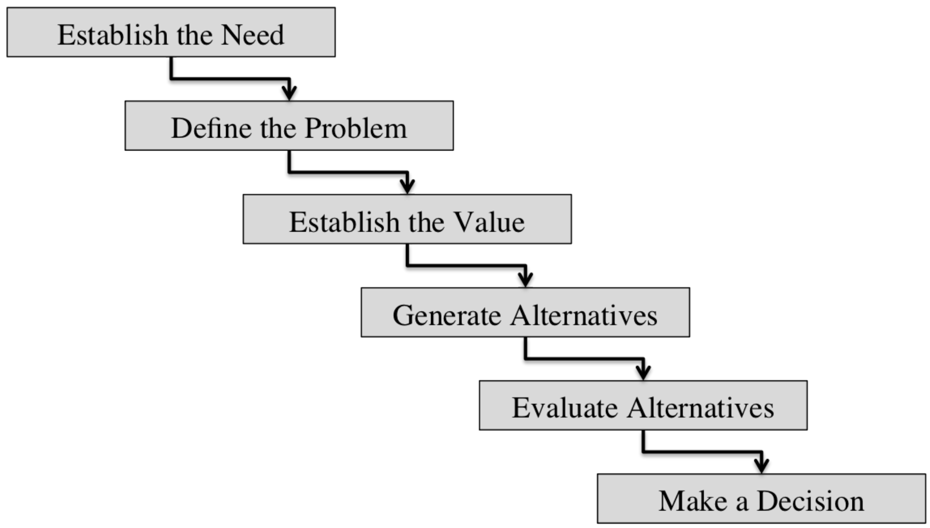

Figure 8: Generic top-down decision making process.

The process of prioritization and down-selection encompasses the final steps of the generic process. The first step is identifying the value metrics that will be used for the prioritization, next the different alternatives must be identified or generated, and then the alternatives must be analyzed and the value metrics must be calculated. Figure 9 displays this prioritization process, which has a decision making matrix as its core. The identified alternatives are the rows of the decision matrix and they could either be provided to the program, could come from research, or be the result of some prior analysis. The metrics that are used to communicate the value of the alternatives are the columns of the decision matrix. For this research, the metrics should be ones that sufficiently communicate readiness risk and performance risk.

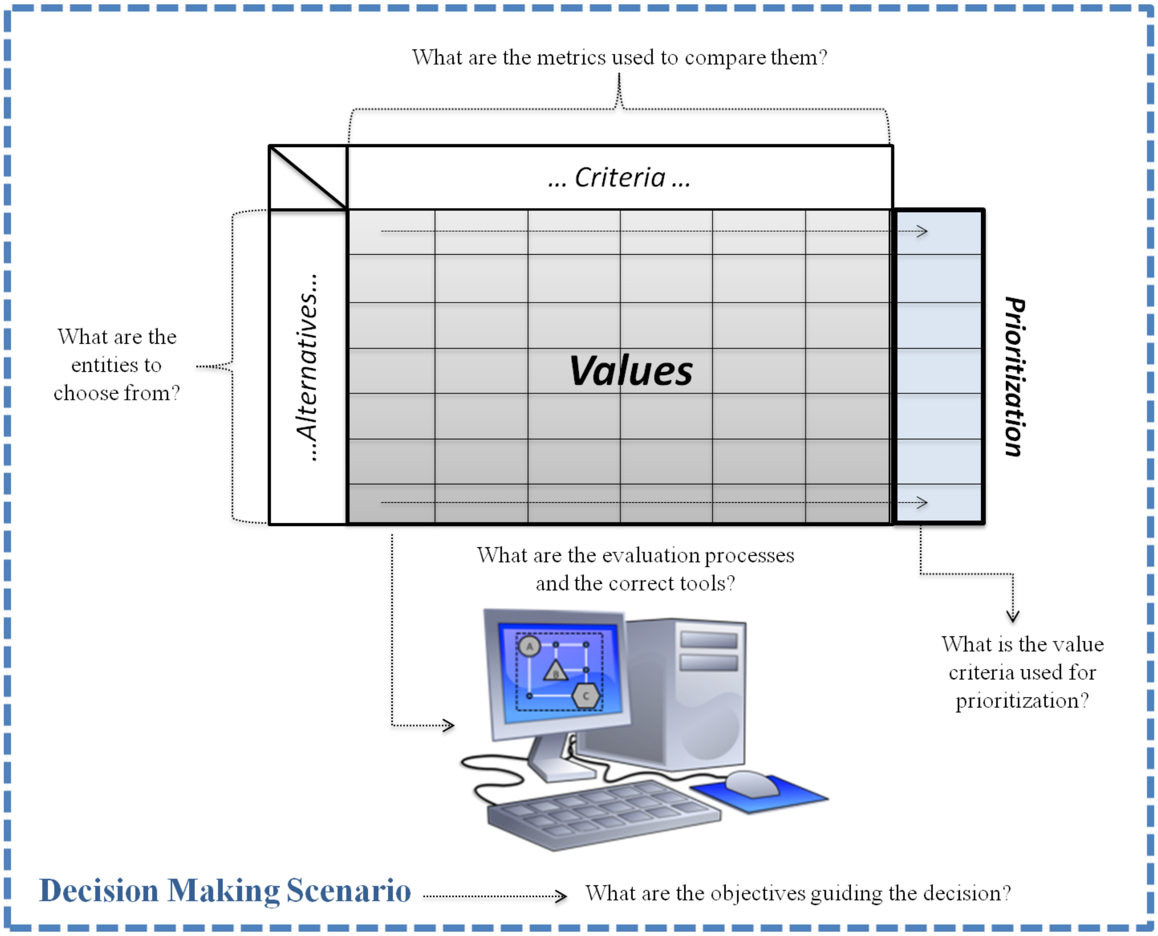

Figure 9: Prioritization process

The middle portion of the decision matrix are the metric values for each of the alternatives under consideration. Population of the metric values requires devising an analysis procedure which utilizes a modeling and simulation environment that captures the system under assessment. For this research, the analysis procedures will outline how the identified risk measures can be calculated if an appropriate modeling and simulation environment is readily available. The modeling and simulation environment must be appropriate in terms of the physics it is able to capture.

The final step of the process, prioritization, is depicted in the right most column of the decision matrix. Prioritization involves creating overall value criteria that synthesizes the information provided by each of the metrics in the decision matrix. This could be accomplished through a single value that is a weighted combination of the other values, through multiple values, or through a series of communication tools that visualize the trade-offs inherent to the problem. Furthermore, the final prioritization is a function of the decision making scenario surrounding the development phase or the program as a whole. Different scenarios include the need to reduce the budget of the program, the need to overshoot established performance goals, the preferences placed upon the different objective metrics, etc. All of this information is then used by decision makers to make the final decision.

As mentioned, the methodology developed within this research is in reality a series of prioritizations. Therefore, it can be thought of as an integration of sequential decision making processes, as visualized in Figure 10. The decisions are not necessarily at the same level, and will therefore not necessarily utilize the same metrics or criteria for prioritization. Therefore, methodology development will encompass the enumeration of the criteria and metrics, determination of the analysis procedures and the required tools, and conducting prioritization for different decision scenarios to demonstrate the dynamic aspect of the methodology. Additionally, when uncertainty surrounds the alternatives, these analysis procedures must incorporate uncertainty quantification procedures and probabilistic analysis techniques.

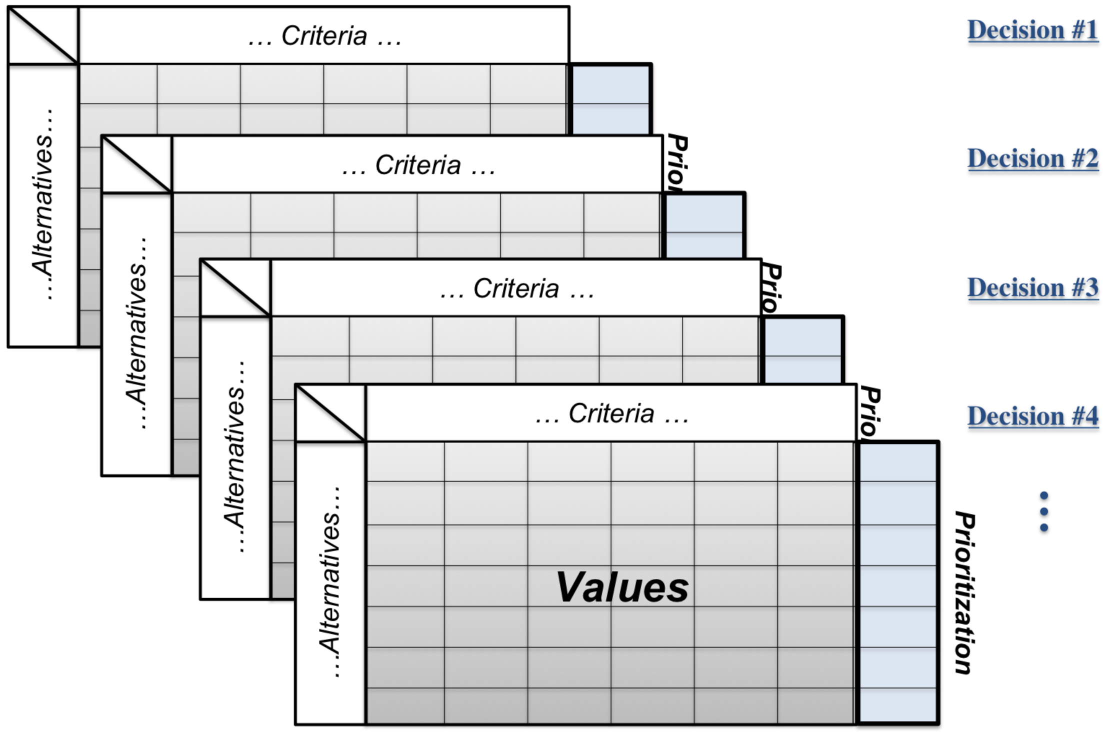

Figure 10: Methodology formulations a cascade of decision making processes.

The enumeration of the development phases, their corresponding key decisions, and the recognition that the methodology is a series of prioritizations that support risk-informed decision making led to the architecture of the methodology. The methodology outline is provided in Figure 11, where each step of the development process has been identified and categorized into one of the four defined development phases. Steps in the process highlighted in green are those steps that will be addressed within this research and further defined through formal methodology formulation in the following chapter.

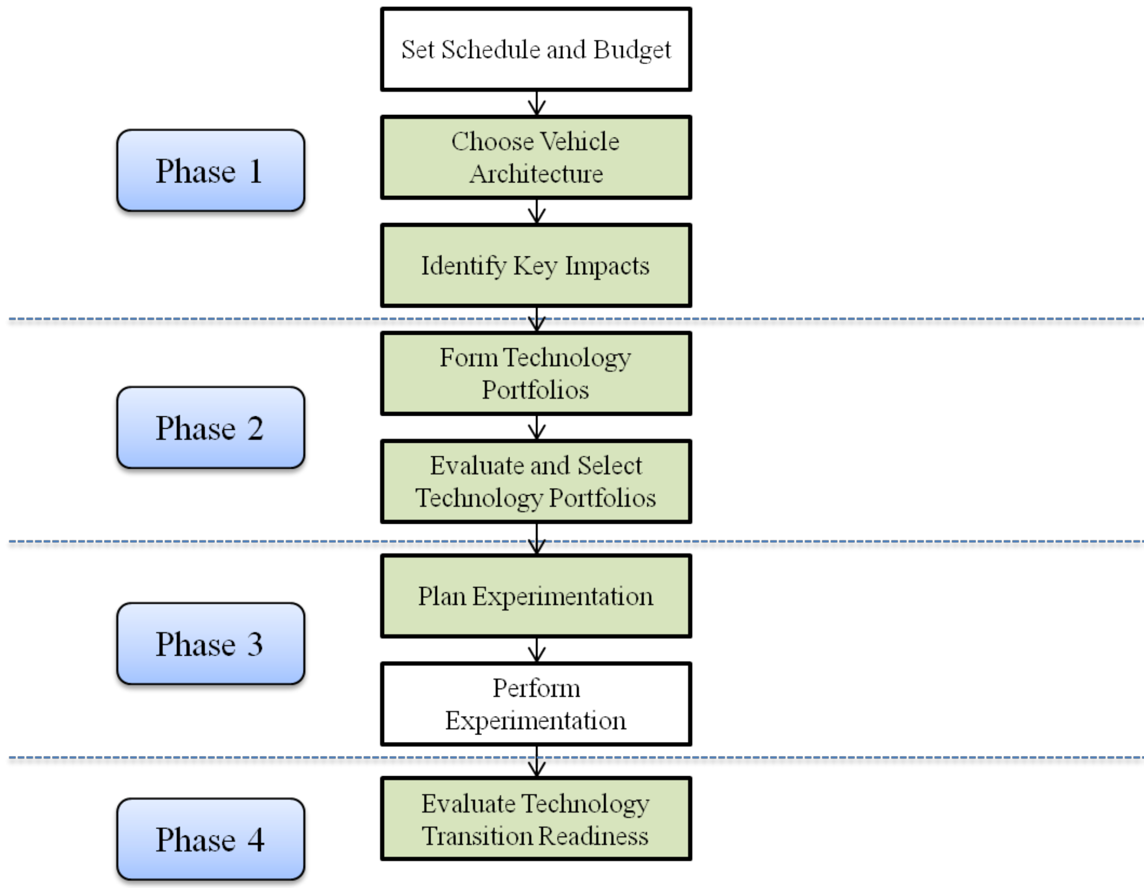

Figure 11: Architecture of the risk-informed technology development methodology developed within this research.

Based upon the provided problem formulation, an investigation into the relevant background literature was conducted to discover existing methodologies that address aspects of technology development decision making. The primary methodology discovered to be the most all-inclusive with respect to technology development decisions was the Technology Identification, Evaluation, and Selection (TIES) methodology developed by Kirby and Mavris at the Georgia Institute of Technology. TIES encompasses both architecture selection and technology selection and provides some key processes that could be leveraged for this methodology. A depiction of the steps within the TIES methodology are shown in Figure 12 while details of the methodology are provided in Appendix C.

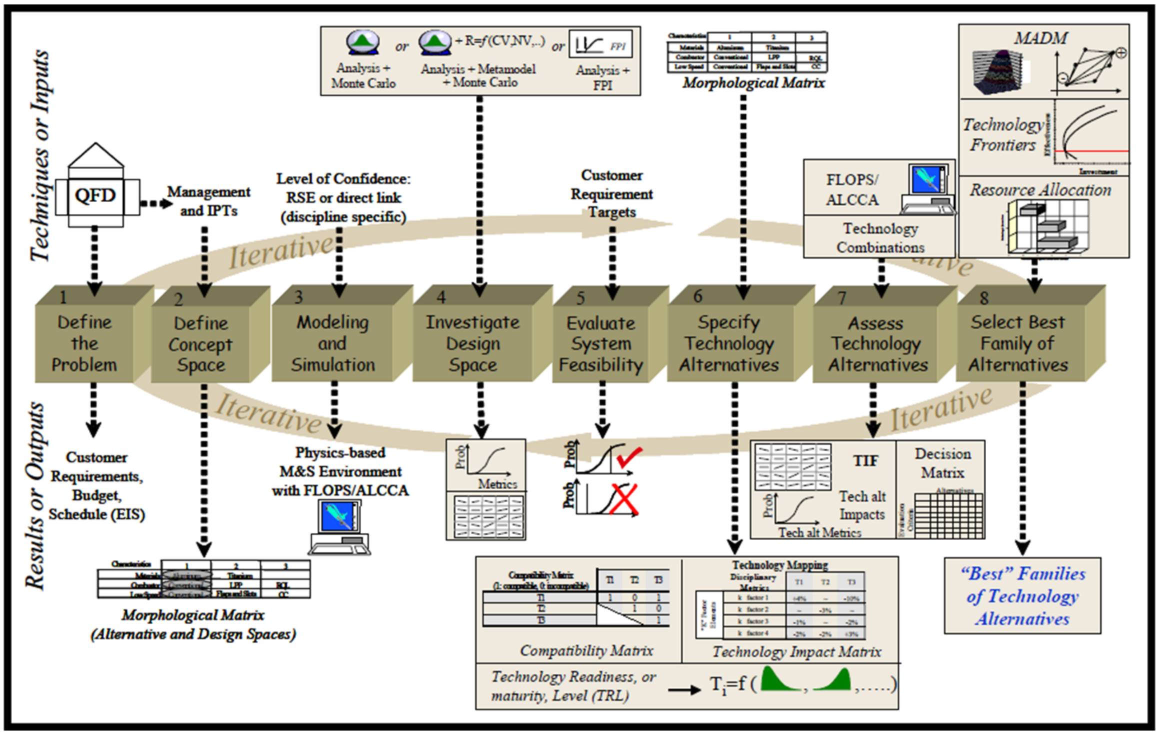

Figure 12: Technology Identification, Evaluation, and Selection Methodology Depiction.

The TIES methodology incorporates some probabilistic assessment, but does not focus on the advantages of utilizing quantitative uncertainty analysis techniques to provide risk-informed technology development decisions. Furthermore, while Kirby and Mavris do acknowledge the connection between technology readiness and performance uncertainty, the TIES methodology does not attempt to synthesize the information communicated by both. The TIES methodology does provide the architecture of a benchmark process that can be built upon to cover more phases of technology development and include more analysis and resulting information.

The methodology created within this research aims to encompass all of the identified technology development phases and capture relevant readiness and performance risk information throughout each phase. Therefore, the TIES methodology is leveraged because it does capture several of the development phases and includes probabilistic analysis techniques. However, now a greater emphasis will be given to the uncertainty surrounding the technologies and its impact on the system assessments and resulting development decisions. Furthermore, a process that enables the reduction of the uncertainty through experimentation is desired, so additional steps will be added. The assessment techniques of these additional steps will focus on characterizing, analyzing, and reducing the uncertainty sources.

Appropriate quantitative performance uncertainty analysis approaches and technology readiness assessment approaches were identified in the literature in order to identify relevant measures and assessment procedures that can be leveraged for this methodology. The rest of this chapter will provide relevant background information on technology readiness and uncertainty quantification to provide a benchmark for further methodology development.

2.1 Readiness Metrics and Assessments

Assuring system readiness is an important goal of system development. Readiness of an entire system depends on the readiness of each of its subsystems, components, and technologies. Readiness has many aspects, all of which need to be assessed and tracked throughout the development process. The current state of the art for tracking program or technology readiness is through the utilization of well-defined metrics. Many metrics exist and much debate exists in the literature over which metrics are best suited for ensuring the proper calculation and communication of individual technology readiness and overall system readiness.

The first noticeable debate in the literature surrounds the terms readiness and maturity; therefore, the terms readiness and maturity must be clearly defined. Commonly, these two terms are used interchangeably and no delineation of their definitions is made. However, Smith [104] notes that in the context of software engineering they are not the same and should not be used to mean the same thing. Maturity refers to the general status of a technology, or entity, without any specific application in mind. Readiness, on the other hand, implies an entity has a high level of maturity with regards to a specific application. Therefore, a technology could have a high maturity level, but in the context of an application it has not been previously considered (or developed) for it has a low readiness level.

For the rest of this thesis the term *technology readiness* will refer to "the maturity of a technology with respect to the specific system under development", and the term *system readiness* will be defined as "the overall maturity of the system being developed to meet the given program objectives". This remainder of this chapter provides descriptions of the most common readiness metrics, readiness assessment methodologies, and approaches for determining metric values found in the literature.

2.1.1 Technology Readiness Level

The current figure of merit used within NASA and the DOD to represent the readiness of an entity under development is the Technology Readiness Level (TRL). Stan Sadin of the Office of Aeronautics and Space Technology (OAST) developed the concept of TRL in the late 1970s [68]. Originally, it was developed as a device to enable comparison of two different technologies with respect to their maturity levels and had 6-7 levels. The use of the TRL scale expanded as programs and initiatives, such as the Civil Space Technology Initiative and the Space Exploration Initiative, were created after the Challenger incident. These initiatives required the utilization of a more structured approach for maturing advanced technologies.

Eventually, the TRL scale expanded from its original version to its current status of a 9-level metric. The 9-level system was formalized via a white paper released in 1995 by Mankins. In this paper, Mankins formally defined TRL as a "systematic

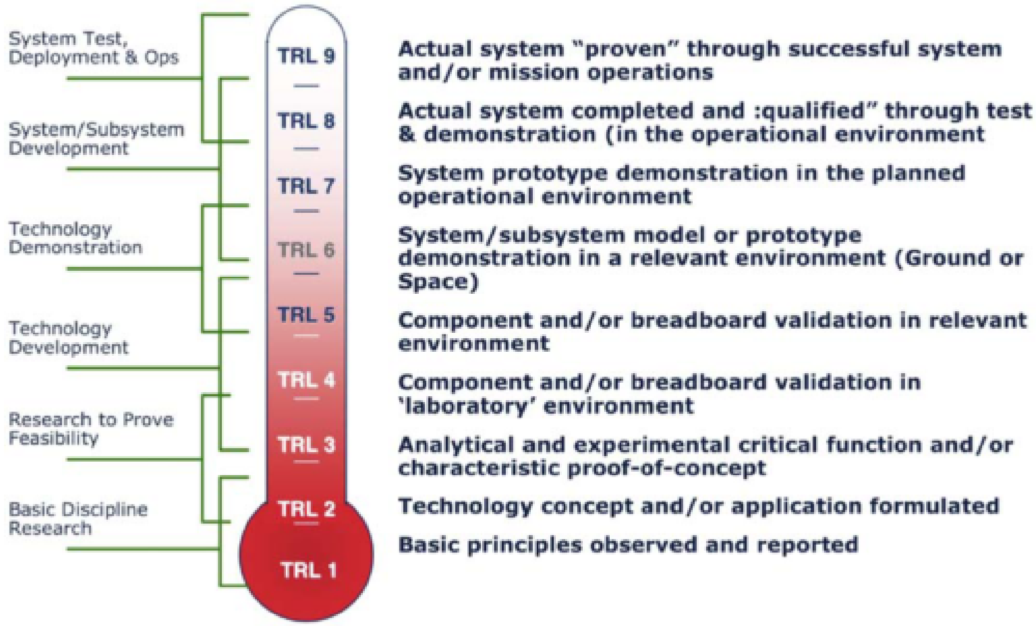

Figure 13: Formal TRL definitions.[Reproduced from [68]]

metric/measurement system that supports assessments of the maturity of a particular technology and the consistent comparison of maturity between different types of technologies" [64]. The document provides brief summaries of the type of understanding that should be achieved at each level, examples of relevant experimentation for each level, and comparative cost estimates. However, the document does not provide a detailed description of each level and the characteristics that define it.

Expansion of the use of the TRL scale continued into the millennium. The DOD formally adopted the TRL scale in 2000 following a recommendation the U.S. General Accountability Office made in 1999 [68]. Several European countries adopted versions of the TRL scale, and by 2006 it was formally adopted worldwide. Through time, the TRL scale has provided a way to assess technology maturity and readiness, and communicate it to others who may have no disciplinary knowledge of the entity in question. More detailed definitions of each level within the scale have been developed and are summarized in Figure 13.

Technologies categorized as TRL 1, TRL 2, or TRL 3 are considered low-TRL.

TRL 1 represents the lowest level of understanding or maturity. The result of research at this level is the comprehension of the basic governing physics. The cost to achieve TRL 1 is not consistent and can range from very low to very high depending on the characteristics of the discipline. At TRL 2, practical applications of the technology are identified or determined (invented). Development of a proof of concept for these applications is considered TRL 3 when active research and development is achieved. Cost associated with TRL 2 is usually considered low and cost associated with TRL 3 is low to moderate. Together, TRL 2 and TRL 3 would represent a small to modest fraction of the total system cost.

Technologies categorized as TRL 4, TRL 5, or TRL 6 are considered mid-TRL. These levels are focused around integrating the pieces of the technology concept together, first at sub-scale and eventually at a realistic scale. At TRL 4 the pieces must be integrated at the component level and be representative to an application identified during the low-TRL studies. At TRL 5 they must be integrated with reasonable supporting elements (i.e. complete subsystem) to enable testing of the full system in a simulated or comparably realistic environment. The pieces must be further integrated and elevated to a prototype of the entire system and tested in a relevant environment at TRL 6. Cost associated with mid-TRL tasks is much higher than those associated with low-TRL tasks. The cost to achieve TRL 4 from TRL 3 could be much more than the total cost to achieve TRL 3. The cost to achieve TRL 5 is usually considered moderate to high while the cost to achieve TRL 6 is usually high.

Technologies at TRL 7, TRL 8, and TRL 9 are high-TRL technologies and represent a significant increase in TRL from the mid-TRL range. Achieving TRL 7 requires the fabrication of an actual complete system prototype of a planned application and testing in the expected operational environment. TRL 8 usually represents the end of system development by applying the technology to an actual system that will be used, not just a prototype. Successfully achieving TRL 8 usually implies realization of TRL 9 as well, because that system will eventually be utilized. Cost connected to TRL 7 is considered very high, and in most cases would be a significant portion of the total development cost. TRL 8 costs are typically very high as well, and could be greater than the combined costs of all prior TRL levels by a factor of 5-10. TRL 9 costs are also high, but significantly lower than the costs associated with TRL 8.

2.1.2 TRL Shortcomings

The TRL scale provides a formal system for assessing and communicating technology maturity or readiness, but there is debate on whether it is the most appropriate metric for the task at hand. Smith [104] describes four reasons TRL is not always a proper maturity metric, specifically for the software development industry. His first argument is TRL combines aspects of all system characteristics into one metric, especially when it is in the high-TRL range, which makes it hard to determine how each of the characteristics is affecting the overall TRL of the technology, or individual system, in question. Smiths second argument addresses the criticality of the technology in question with respect to success of the entire system. TRL does not attempt to include this aspect into its assessment. His third argument is specific to the definition of TRL 9. For spacecraft or aircraft, once the system has flown a relevant mission and requires no further alterations it is considered TRL 9. However, software and other equivalent disciplines continuously change throughout its lifecycle, even after it has been officially deployed. TRL does not provide a way to handle this continual degradation in readiness. Finally, Smith's last argument relates to the varying level of importance of readiness throughout the acquisition life-cycle of a system, and he states TRL does not provide a way to incorporate this in its current form.

Mankins, the same person to formalize the TRL scale in the 1995 white paper [64] and subsequent papers [65, 68], has also criticized its ability to fully represent all aspects of readiness. First, he states TRL does not contribute to assessing the riskiness of developing the technology in question [68]. His second argument is TRL does not provide an assessment of how difficult it will be to mature a technology and move from one level of the scale to the next [65, 67]. Finally, he argues a complete metric would include information on the expected importance, or criticality, of the technology in question to its system application [67].

Meystel et al. feel the early and mid TRL levels serve as a check-list of requirements, while the later stages (beginning at level 6) provide the basis of a framework for validating the quality of the entire system [73]. They go on to state that metrics for intelligent, autonomous systems must include aspects measuring their operating environment as well.

Sauser et al. (2008) summarizes the issues brought up by various sources about TRL into three main complaints. The first is TRL does not provide the ability to represent integration difficulties, the second is the lack of assessment of difficulty to move through the scale, and the third is the criticality of the current TRL of a technology to the readiness of an entire system. [97] Jimenez et al. also argues that TRL does not adequately address integration aspects of system or technology readiness and suggest that the TRL scale is not meant to be utilized as a way to assess the readiness of a system composed of multiple immature technologies[49].

Tan et al. [106] criticized the ambiguity of the formal definitions of each level of the TRL scale, stating it could not be consistently applied throughout agencies. They state that each agency using the TRL scale is interpreting the meaning of the definitions in different ways, and producing new definitions tailored to their needs. While this is not necessarily a problem within a single agency, it could create problems when comparing maturity of two technologies that were assessed by different entities. Tan et al. provided a comparison of interpretations of the TRL levels for four different government agencies, and this figure is reproduced in Figure 14.

Table 2 summarizes the identified shortcomings of the TRL scale. Descriptions

TRL	*National Aeronautics and Space Administration (NASA) [Mankins, 2002]*	*Department of Defense (DoD) [DoD, 2005]*	*Department of Energy (DoE) [Carmack and Pasamehmetoglu, 2008]*	*North Atlantic Treaty Organization (NATO) [NATO, 2006]*
0	N/A	N/A	N/A	Basic research with future military capability in mind
1	Basic principles observed and reported	Basic principles observed and reported	Initial concept verified against first principles and evaluation criteria defined.	Basic principles observed and reported in context of a military capability shortfall
2	Technology concept and/or application formulated	Technology concept and/or application formulated	Technical options evaluated and parametric ranges are defined for design	Technology concept and / or application formulated
3	Analytical and experimental critical function and/or characteristic proof-of-concept	Analytical and experimental critical function and/or characteristic proof of concept	Success criteria and technical specifications are defined as a range	Analytical and experimental critical function and / or characteristic proof-of-concept
4	Component and/or breadboard validation in laboratory	Component and/or breadboard validation in laboratory environment	Fuel design parameters and features defined	Component and/or "breadboard" validation in laboratory/field (eg ocean) environment
5	Component and/or breadboard validation in relevant environment	Component and/or breadboard validation in relevant environment	Process parameters defined	Component and/or "breadboard" validation in a relevant (operating) environment
6	System/subsystem model or prototype demonstration in a relevant environment (ground or space)	System/subsystem model or prototype demonstration in a relevant environment	Fuel safety basis established	System/ subsystem model or prototype demonstration in a realistic (operating) environment or context
7	System prototype demonstration in a space environment	System prototype demonstration in an operational environment	All qualification steps completed and fuel is licensed	System prototype demonstration in an operational environment or context (eg exercise)
8	Actual system completed and "flight qualified" through test and demonstration (ground or space)	Actual system completed and 'flight qualified' through test and demonstration	Reactor full-core conversion to new licensed fuel completed	Actual system completed and qualified through test and demonstration
9	Actual system "flight proven" through successful mission operations	Actual system 'flight proven' through successful mission operations	Routine operations with licensed fuel established	Actual system operationally proven through successful mission operations

Figure 14: Example TRL definitions.[Reproduced from [106]]

of metrics created in attempt to fill in some of these shortcomings will be presented in proceeding sections. Some of these additional metrics are not intended to be all-inclusive measures of maturity or readiness, but rather aim to fill specific identified voids in the TRL system. Therefore,it is suggested that some of these metrics be seen as supplemental to TRL, and in some cases an assessment of TRL is required in order to calculate the new metric.

Table 2: Identified TRL Shortcomings

TRL Shortcomings	Source
TRL combines aspects of the entire system characteristics into one metric, which makes it hard to determine how each of the characteristics is affecting the overall TRL of the entity in question	Smith[104],Meystel et al.[73]
Does not mention the criticality of the technology with respect to the success of the entire system	Smith[104], Mankins[67]
TRL 9 definition does not work for systems that are constantly evolving/adapting/changing, such as software	Smith[104]
Varying level of importance of readiness throughout the acquisition life-cycle not captured	Smith[104]
Does not assess the riskiness associated with the developing technology	Mankins[68]
Does not assess how difficulty it will be to move from one level to the next	Mankins[65, 67], Sauser et al.[97]
Early TRL stages are a checklist of requirements	Meystel et al.[73]
Does not represent integration difficulty	Sauser et al.[97], Jimenez et. al[49]
Ambiguity of definitions makes it difficult to consistently apply it	Tan et al.[106]

2.1.3 Measures of Difficulty

2.1.3.1 Research and Development Degree of Difficulty

Mankins created the Research and Development Degree of Difficulty (R & D^3) to answer the question "How hard will it be to move from one TRL to the next for a given set of research and development objectives?" [67]. It provides a measure of how much difficulty one should expect to encounter during the maturation process of

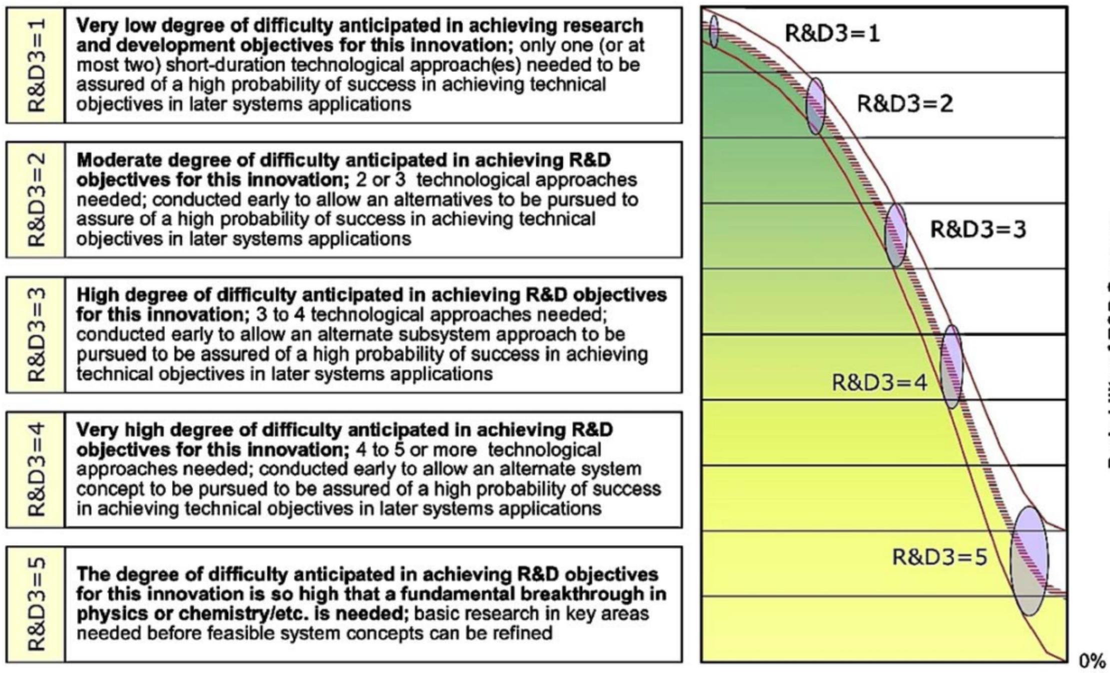

Figure 15: Research and Development Degree of Difficulty Scale.[Reproduced from [67]]

a given technology or entity and suggests the number of approaches R & D managers should pursue at once. Difficulty, in this context, is measured with respect to probability of success (POS) of meeting system concept objectives, performance objectives, reliability objectives, and cost goals under “normal” R& D efforts.

There are five levels of the R & D^3 scale. Level I represents a very low degree of difficulty (POS greater than 95%-99%) in achieving R& D objectives, Level II represents a moderate degree of difficulty (POS greater than 90%), Level III represents a high degree of difficulty (POS greater than 70%-80%), Level IV represents a very high degree of difficulty (POS greater than 50%-60%), and Level V represents a sufficiently high (POS greater than 30%-40%). [65]. Details of the R& D^3 scale can be seen in Figure 15.

2.1.3.2 *Degree of Difficulty*

Advancement Degree of Difficulty (AD^2) attempts to answer the question "What is required to advance the immature technologies from their current TRL to a level that permits infusion into the program within cost, schedule, and risk constraints?" [15] AD^2 provides a description of what will be required to move an entity under development (system, subsystem, technoloty, etc.) from one TRL to a higher TRL. This metric provides information in terms of likelihood of occurrence of an adverse event, cost to ensure that such an event does not occur, and the time required to implement the necessary preventative action.[16] Similarly to R& D^3, the number of recommended development approaches is provided within the definitions of the AD^2 levels.

There are 9 levels of the AD^2 scale. Level 1 corresponds to 0% development risk and suggests that a single development approach is adequate. Level 2, Level 3, and Level 4 correspond to 10%, 20%, and 30% development risk, respectively, and all suggest the pursuance of a single development approach. Level 5 corresponds to 40% development risk and suggests dual development approaches be pursued to ensure high probability of success. Level 6 reflects 50% development risk and it is suggested that dual development approaches be pursued to achieve a moderate degree of confidence for success. Level 7 and Level 8 correspond to 60% and 80% development success, respectively, and suggest multiple development routes be pursued. Level 9 represents the highest degree of difficulty and corresponds to 100% development risk, which means no viable development approaches exist and basic research is needed.

2.1.4 Measures of Importance

2.1.4.1 *Technology Need Value (TNV)*

Mankins created the Technology Need Value (TNV) metric to provide an assessment of the expected importance of a given technology advancement to the success of anticipated system application[67]. He states that determination and communication of the relative importance of all technologies of interest to a program or system is essential for good R & D management, and TNV can fill that void. Importance, with respect to TNV, is expressed in terms of either the importance to the ultimate system application or the importance of the potential information the technology effort can provide for future management decisions.

TNV is best thought of as a weighting factor based on the qualitatively assessed importance of the technology[65, 67]. There are five levels of the TNV scale and each has a corresponding weighting factor in the form of a percentage, a qualitative assessment of importance, and a qualitative assessment of when the information is needed by management. Detailed definitions of each level are provided in Figure 16.

Technology Need Value	Weighting Factor	Description
TNV-1	40%	The technology effort is **not critical at this time** to the success of the program— the advances to be achieved are useful for some cost improvements; However, the information to be provided is not needed for management decisions until the far- term
TNV-2	60%	The technology effort is **useful** to the success of the program—the advances to be achieved would meaningfully improve cost and/or performance; However, the information to be provided is not needed for management decisions until the mid- to far- term
TNV-3	80%	The technology effort is **important** to the success of the program—the advances to be achieved are important for performance and/or cost objectives AND the information to be provided is needed for management decisions in the near- to mid- term
TNV-4	100%	The technology effort is **very important** to the success of the program; the advances to be achieved are enabling for cost goals and/or important for performance objectives AND the information to be provided would be highly valuable for near-term management decisions
TNV-5	120%	The technology effort is **critically important** to the success of the program at present—the performance advances to be achieved are enabling AND the information to be provided is essential for near-term management decisions

Figure 16: Tecnology Need Value.[Reproduced from [67]]

2.1.4.2 Critical Technology Element

The DOD uses the term Critical Technology Elements to identify technologies important to a system under development. They state that a technology element is classified as critical if "the system being acquired depends on this technology element to meet operational requirements (within acceptable cost and schedule limits) and if the technology element or its application is either new or novel or in an area that poses major technological risk during detailed design or demonstration"[8]. CTE is not a metric like TNV, as it does not have a scale. Instead, CTE is a classification that a technology or entity receives if it is determined to be "critical".

A set of six questions is provided to determine if a technology is a CTE. An answer of "yes" to the first question in addition to any question between two and six results in the classification of a CTE. The questions are:

1. Does the technology have a significant impact on an operational requirement, cost, or schedule?

2. Does this technology pose a major development or demonstration risk?

3. Is the technology new or novel?

4. Has the technology been modified from prior successful use?

5. Has the technology been repackaged such that a new relevant environment is applicable?

6. Is the technology expected to operate in an environment and/or achieve a performance beyond its original design intention or demonstrated capability?

2.1.5 Measures of Integration Readiness

2.1.5.1 Integration Readiness Level

Sauser et al.(2006) created the Integration Readiness Level (IRL) metric. IRL is defined as a "measurement of the interfacing of compatible interactions for various technologies and the consistent comparison of the maturity between integration points" [96]. The assigned value of the IRL metric to a technology under development describes its integration maturity with respect to another technology that is to be included in the same system.

Following the initial creation of IRL, Sauser et al.(2010) formalized the integration shortcomings of TRL into a set of requirements for an integration maturity metric (IMM). The IMM requirements are: [95]

1. IMM shall provide an integration specific metric, to determine the integration maturity between two configuration items, components, and/or subsystems.

2. IMM shall provide a means to reduce the risk involved in maturing and integrating a technology into a system.

3. IMM shall provide the ability to consider the meeting of system requirements in the integration assessment so as to reduce the integration of obsolete technology over less mature technology.

4. IMM shall provide a common platform for both new system development and technology insertion maturity assessment.

The identification of these requirements led to a reevaluation of the IRL metric. As it was initially defined IRL had 7 levels, with the final level defined as "the integration of technologies has been verified and validated with sufficient detail to be actionable"[96]. It was determined that IMM Requirement 4 was not fully met because there was no indication in the existing IRL scale of when integration is complete. Therefore, the IRL scale was extended to include a Level 8 and Level 9 that mirrored the definitions of TRL 8 and TRL 9.Definitions of each of the nine levels of IRL is shown in Table 3.

Table 3: Integration Readiness Level Definitions and Descriptions[49]

IRL	Definition	Descriptions
9	Mission Proven	Integrated technologies used in system environment successfully
8	Mission Qualified	System-level demonstration in relevant environment
7	Verified and Validated	Meet integration requirements such as performance, throughput and reliability
6	Accept, Translate, and Structure Information	Specify what information to exchange, identify received data, translate between data structures
5	Control	One or more technologies establishes, maintains, and terminates integration
4	Quality and Assurance	Data sent is the same as data received, checking mechanism in place
3	Compatibility	Common language, technologies communicate interpretable data
2	Interaction	Selection of a signaling method, technologies interact over a medium
1	Interface	Selection of a medium for integration

2.1.5.2 Integration based on TRL

Jimenez and Mavris (2014) noted four shortcomings of the IRL metric. First, they state that the IRL metric is not generalizable to all technologies or systems and it is limited to datacentric applications only. Second, they note that the IRL definitions provide no information about the architecture of the system, and the entire integrated system is only mentioned in Level 8 and Level 9. Third, they point out that the IRL metric is intended to be independent of TRL metric, which they feel is a fundamental flaw because integration can be seen as a sub-attribute of TRL. Lastly, they call attention to the aggregation of TRL and IRL to form a System Readiness Level(SRL) measure (this will be discussed in a following section). [46]

Jimenez and Mavris proposed that these identified issues could be overcome by considering technology integration as a sub-attribute of technology maturation, and they developed a set of integration descriptions by assessing the various TRL definitions utilized by government entities and industry. Instead of producing a new metric or measure of integration, detailed descriptions of what is expected with regards to integration were formulated for each of the nine TRL levels. The descriptions are intended to be used as a way to characterize technology integration, a way to articulate an integration roadmap, and as integration criteria for achievement of a given TRL.

Figure 17 summarizes how integration readiness progresses with TRL according to Jimenez and Mavris. Their definitions aim to capture a variety of integration aspects. Included in the definitions are technology architecture status, system architecture status, modeling capabilities of technology impact, modeling of technology interactions with other pieces of the system, hardware integration status, and amount of existing integration uncertainties.

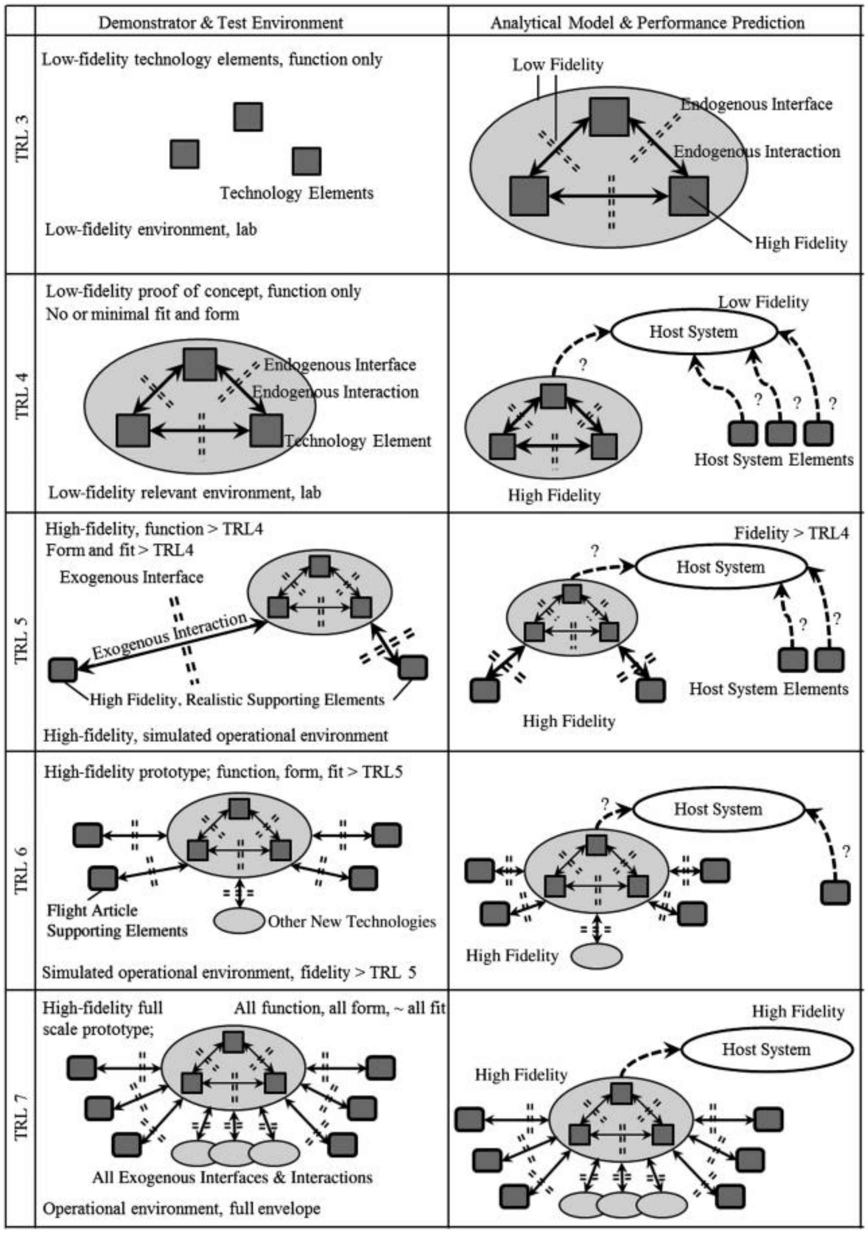

Figure 17: Aspects of integration relevant to TRL.[Reproduced from [46]]

2.1.6 Measures of System Readiness

2.1.6.1 System Readiness Level (Sauser)

Sauser et. al [96] created the Systems Readiness Level (SRL) to provide a metric to measure the overall readiness of a system that is composed of multiple technologies at varying levels of maturity. As previously mentioned, some interpret the TRL metric to be a measure of maturity and integration readiness; however, these authors believe that technologies with similar maturity, or TRLs, do not necessarily have similar levels of integration maturity. Therefore, the SRL metric is comprised of both the TRL metric and the IRL metric. There are five general levels of SRL and the scale can be seen in Figure 18.

A mathematical formulation for calculating SRL, as a function of TRL and IRL, is provided in Tan et al [106]. The process for calculating SRL follows three steps:

1. Normalize the TRLs and IRLs of each component (technology) from 0-1
2. Produce component SRL matrix by multiplying TRL and IRL
3. Produce a composite SRL by averaging all component SRLs

Equation 1 and Equation 2 show the first step mathematically, Equation 3 shows the second step, and 4 shows the third.

$$[TRL]_{nX1} = \begin{bmatrix} TRL_1 \\ TRL_2 \\ ... \\ TRL_n \end{bmatrix} \xrightarrow{normalize} \begin{bmatrix} TRL_1 \\ TRL_2 \\ ... \\ TRL_n \end{bmatrix} \tag{1}$$

$$[TRL]_{nX1} = \begin{bmatrix} IRL_{11} & IRL_{12} & ... & IRL_{1n} \\ IRL_{21} & IRL_{22} & ... & IRL_{2n} \\ ... & ... & ... & ... \\ IRL_{n1} & IRL_{n2} & ... & IRL_{nn} \end{bmatrix} \xrightarrow{normalize} \begin{bmatrix} IRL_{11} & IRL_{12} & ... & IRL_{1n} \\ IRL_{21} & IRL_{22} & ... & IRL_{2n} \\ ... & ... & ... & ... \\ IRL_{n1} & IRL_{n2} & ... & IRL_{nn} \end{bmatrix} \tag{2}$$

SRL	Name	Definition
5	*Operations & Support*	Execute a support program that meets operational support performance requirements and sustains the system in the most cost-effective manor over its total life cycle.
4	*Production & Development*	Achieve operational capability that satisfies mission needs.
3	*System Development & Demonstration*	Develop a system or increment of capability; reduce integration and manufacturing risk; ensure operational supportability; reduce logistics footprint; implement human systems integration; design for producibility; ensure affordability and protection of critical program information; and demonstrate system integration, interoperability, safety, and utility.
2	*Technology Development*	Reduce technology risks and determine appropriate set of technologies to integrate into a full system.
1	*Concept Refinement*	Refine initial concept. Develop system/technology development strategy

Figure 18: System Readiness Levels.[Reproduced from [96]]

$$\begin{bmatrix} SRL_1 \\ SRL_2 \\ ... \\ SRL_n \end{bmatrix} = \begin{bmatrix} IRL_{11} & IRL_{12} & ... & IRL_{1n} \\ IRL_{21} & IRL_{22} & ... & IRL_{2n} \\ ... & ... & ... & ... \\ IRL_{n1} & IRL_{n2} & ... & IRL_{nn} \end{bmatrix} \times \begin{bmatrix} TRL_1 \\ TRL_2 \\ ... \\ TRL_n \end{bmatrix} = \begin{bmatrix} IRL_{11}TRL_1 + IRL_{12}TRL_2 + ... + IRL_{1n}TRL_n \\ IRL_{21}TRL_1 + IRL_{22}TRL_2 + ... + IRL_{2n}TRL_n \\ ... \\ IRL_{n1}TRL_1 + IRL_{n2}TRL_2 + ... + IRL_{nn}TRL_n \end{bmatrix} \tag{3}$$

$$SRL = \frac{SRL_1 = SRL_2 + ...SRL_n}{n} = \frac{\sum_{i=1}^{n} SRL_i}{n} \tag{4}$$

2.1.6.2 System Readiness Level - UK Ministry of Defense

The United Kingdom (UK) Ministry of Defense created a second System Readiness Level metric (SRL-UK). SRL-UK provies an understanding of the remaining work required to mature the project, or system, of interest[16]. SRL-UK is a nine level scale, with nine being the highest level of readiness. Assessment of SRL-UK includes consideration of the TRL levels of each component within the system, and follows the notion that the overall readiness of the system must be less than or equal to the readiness of each of its components. A single SRL-UK value is not produced for an entire system; instead, an SRL-UK "signature" is produced that displays the level of system readiness with respect to multiple disciplines of the system.

2.1.7 Additional Readiness Measures

2.1.7.1 Manufacturing Readiness Level

Manufacturing Readiness Level (MRL) is a measure designed to assess the maturity of a technology from a manufacturing perspective. It provides the ability to represent the manufacturing, production, quality assurance, and industrial functions required to reach operational status. MRL was developed to address the need for manufacturing evaluation throughout all phases of system development and provides decision makers with a common understanding of the associated manufacturing risks of the system.

There are ten levels to the MRL scale. Each level is defined in terms of the maturity of the manufacturing plan, the ability to manufacture an entity, the fidelity of the manufactured entity, and the environment it is manufactured in. For example, Level 4 is defined as "Capability to produce the technology in a laboratory", while Level 7 is defined as "Capability to produce systems, subsystems, or components in a production representative environment". [5]

2.1.7.2 Excluded Readiness Measures

Many measures have been identified that attempt to capture other aspects of technology or system readiness or maturity. Examples of such include: Design Readiness Level, Software Readiness Level, Operational Readiness Level, Human Readiness Level, Capability Readiness Level, Organizational Readiness Level, and Programmatic Readiness Level[16]. However, limited information has been found on the definitions of these metrics, what they intend to capture, and how they are assessed. Therefore, they will not be considered for the remainder of this thesis.

2.1.8 Readiness Processes

In addition to singular scales or metrics developed to capture readiness and maturity, there are also formal processes for evaluating readiness. Many of these processes utilize some of the previously enumerated readiness metrics. The proceeding subsections will highlight a few key processes found in the literature.

2.1.8.1 Integrated Technology Analysis Methodology

Mankins states that a common management challenge facing projects is the ability to compare immature technologies and mature technologies with respect to anticipated performance, reliability, and cost. He states that detailed knowledge of these attributes are usually known solely by technology specialists, and there is a need for a discipline-neutral methodology that enables the assessment and comparison of different types of technologies. To address this issue, the Integrated Technology Analysis Methodology (ITAM) was created. [66]

ITAM is comprised of four major elements. The first element is the formulation of a hierarchy of subsystems and technologies for all of the competing systems, the second element is the determination of discipline-neutral metrics, the third element is the calculation of the Integrated Technology Index (ITI) for each system, and the fourth element is the ranking of all systems according to ITI. Therefore, the ultimate output of ITAM is the calculation of the ITI metric for all systems.

ITI is defined as a quantitative measure of "the relative technological challenge inherent in various advanced system concepts". It is a function of the discipline-neutral metrics mentioned in ITAM's second element. These metrics are TRL, R & D^3, and TNV, which have previously been defined, and the additional metric ΔTRL, which is the difference in the current TRL and the desired TRL. The equation for the calculation of ITI is shown in Equation 5.

$$ITI = \frac{\sum_{SubsystemTechnologies}(\Delta TRL \times R\&D^3 \times TNV)}{Total\#ofSubsystemTechnologies} \tag{5}$$

2.1.8.2 *Technology Readiness and Risk Assessment*

System and technology development decision makers need to be able to make clear, well-documented assessments of technology readiness and risk[67]. Mankins (2009) states that a methodology for assessing technology readiness and risk should have the characteristics of clarity, transparency, crispness, and usefulness in program advocacy. He found that of the methods he considered, none met these characteristics simultaneously. Therefore, Mankins developed Technology Readiness and Risk Assessment (TRRA).

TRRA makes use of previously defined metrics ΔTRL, TNV, and R & D^3. Risk assessment is displayed on a risk matrix, where the y-axis is a measure of probability of R & D failure and the x-axis is a measure of the consequence of R & D failure. Mankins uses R & D^3 as the measure of probability of failure and $TNV \times \Delta TRL$ as the measure of consequence. Each technology that is a part of the R & D program has unique x and y values and can be plotted on the risk matrix which enables a decision maker to compare technologies against one another with regards to the risk they add to the program.

2.1.8.3 *Technology Readiness Assessment*

The DOD uses a process called Technology Readiness Assessment (TRA) to assess the readiness of critical technologies to be implemented into a system of interest. The method is a metrics-based, subject matter expert (SME) driven process that provides guidance regarding the identification of CTEs.

2.1.8.4 *Technology Assessments*

Technology Assessments (TA) is a formal method for assessing and comparing technologies in a development program and is based on TRL assessments with an added measure of difficulty, AD^2. The TRL assessment is done by evaluating all elements in the program's Work Breakdown Structure (WBS) according to the TRL sub-attributes of demonstration unit fidelity, description, and environment. The unit description is expressed in terms of fit, form, and function, otherwise referred to as F3. F3 can be traced to military configuration standards where fit refers to the physical interface with other items, form refers to the physical characteristics, and function refers to the actions an item was designed to perform[49].

2.1.8.5 Risk Identification, Integration, and Illities

Risk Identification, Integration, and Illities (RI3) is a methodology that provides the capability to identify technical risks that arise due to the introduction of new technologies into a system. The method was developed based on case studies, lessons learned, and defined best practices that resulted from a US Air Force (USAF) development team. The methodology assesses risk by enumerating a set of questions in the nine ilities areas to be answers, and it utilizes a risk matrix to display the risk analysis results. [16]

2.1.9 Approaches for Soliciting Readiness Assessments

The previous sections and sub-sections have identified different metrics that attempt to measure specific aspects of technology or system readiness, as well as methodologies that include one or more of these metrics. Most readiness metrics mentioned are captured with a qualitative, ordinal scale. The existing literature shows two main methods for determination of qualitative metric values:

1. SME description-based

2. Calculator-based approaches

These methods will be discussed in the proceeding subsections.

2.1.9.1 SME description-based evaluations

Most readiness metrics discussed have a number of different levels that are characterized, in part, by qualitative definitions. If no quantitative measure is provided to accompany the qualitative definition, or no means to assess the quantitative measure exists, then assignment of a metric value must be done by engineering judgment. Ideally this judgment would be done by, or influenced by, a subject matter expert (SME). Tan et al. notes that SME input can be incorporated in three different manners[106]. The first approach is individual estimation, where a SME estimates the metric value on their own and provides the value to the analyst. The second approach is a group discussion estimation, where a meeting is held for a group of SMEs and they ultimately agree on a single value for the metric. The third method is an individual-group estimation, where a group of SMEs individually assess the metric value and then combine their assessments to arrive at a single value, or potentially distribution of values.

SMEs assessments can be based on sub-attributes identified in the metric descriptions. In many cases a metric aims to capture one aspect of readiness, but that single aspect can be represented by several sub-attributes. A closer examination of the previously provided basic TRL definitions (Figure 13) leads to an immediate identification of three sub-attributes being tracked: number of integrated parts tested, relevance of the testing environment, and fidelity of test objective. A SME using these basic TRL definitions could decide to assign a TRL value based on how the previous research or experimentation maps to the three sub-attributes.

Definitions that provide more detail will inherently have more sub-attributes that can be used for metric assessment. Increasing the number of sub-attributes that exist for a given metric provides an advantage because it gives SMEs a better idea of what they should be judging the technology or system on. However, there is also a disadvantage because it is very likely that an entity being developed will not meet all sub-attribute requirements for a given value simultaneously. Therefore, it may become difficult for SMEs to arrive at a metric value consensus.

2.1.9.2 *Calculator-based approaches*

Calculator-based approaches for metric value determination provide qualitative assessments subject to more evaluation criteria than SME description based assessments. They also provide a means to remedy the problem of assigning a metric value when the evaluation criteria for sub-attributes suggests multiple metric values. Calculators are in many ways synonymous to a checklist of requirements that must be fulfilled in order for an entity to progress through the metric scale. A set of yes or no questions are assigned to each metric level that aim to capture each sub-attribute identified. A SME, or manager in charge of the technology or system, periodically updates the question answers as progress is made. Once all questions for a given level have been answered as yes, which corresponds to completion of all checklist items for that level, then the entity can be assigned that metric value. In some cases there is a final question, or checklist item, for each level that is deemed the exit criteria. The entity cannot receive a certain metric value unless the exit criteria for the previous level has been completed.

The U.S. Air Force Research Laboratory (AFRL) developed a TRL calculator to aid in the determination of appropriate TRL, MRL, and Programmatic Readiness Level (PRL) for technologies in its R & D programs[49]. This is one of the most widely known metric calculators and has been adopted and adapted by other entities, including the U.S. Department of Homeland Security's development of the Science and Technology Readiness Calculator[7]. The AFRL TRL calculator provides a set of tasks pertinent to each level of the TRL scale, as well as specified exit criteria. It provides a visual result of that status of achieving each level through a red/yellow/green color scale. Logic built into the calculator ensures that a given TRL cannot be met until all previous TRL requirements have been met. The AFRL TRL calculator also includes exit criteria for each TRL level. The criteria is displayed in Table 4.

Other metric calculators exist as well. The DOD created an MRL specific calculator, MRL Assist, which provides a series of questions based on the MRL level definitions and calculator tools exist to measure AD^2 and RI3, but limited information is available for their details.

Table 4: AFRL TRL Exit Criteria.

TRL	Exit Criteria
1	Peer reviewed publication of research underlying the proposed concept/application
2	Documented description of the application/concept that addresses feasibility and benefit
3	Documented analytical/experimental results validating predictions of key parameters
4	Documented test performance demonstrating agreement with analytical predictions. Documented definition of relevant environment
5	Documented test performance demonstrating agreement with analytical predictions; Documented definition of scaling requirements
6	Documented test performance demonstrating agreement with analytical predictions
7	Documented test performance demonstrating agreement with analytical predictions
8	Documented test performance demonstrating agreement with analytical predictions
9	Documented mission operational results

2.1.10 Readiness Assessment Observations

The readiness information provided in this chapter outlined the current state of the art in readiness assessments. It was established that TRL is the most prevalent metric used to analyze and communicate technology readiness worldwide. Specific shortcomings of the TRL metric acknowledged in the literature were discussed, and a variety of additional and supplemental metrics were provided. In an effort to investigate the adequacy of using TRL to quantify readiness, a qualitative assessment of the identified TRL shortcomings (displayed in Table 2) was conducted.

The issues regarding technology criticality, importance of readiness with respect to acquisition life-cycle, riskiness of the technology, and difficulty were deemed not directly relevant to measuring the readiness of a single technology. It is important to note that this statement does not mean these characteristics, such as technology criticality or maturation difficulty, are not important with respect to technology development. The statement is only suggesting that they are not specifically relevant to quantifying technology readiness and do not need to be incorporated in a measure of readiness.

After elimination of those issues, the four shortcomings that remain are: checklist of requirements, ambiguity, ability to handle adapting systems, and inclusion of integration readiness. The ability of TRL to handle adapting systems, such as software, has been addressed through the development of software-specific TRL definitions. The inclusion of integration readiness attributes into measures of overall technology readiness could provide a more thorough measure of readiness. It was acknowledged that this can be achieved by utilizing a separate measure of integration readiness, such as IRL, or supplementing TRL with integration-specific readiness attributes as demonstrated by Jimenez et al.

Lastly, it is questioned if the likeness of TRL to a checklist of requirements should indeed be considered a shortcoming for two reasons. First, it was identified as a shortcoming by only one source and the lack of reciprocation from others could mean the community disagrees. Second, its status as a shortcoming is questioned due to the ability to see the benefit a requirements list could provide when assessing readiness. With that said, it is also acknowledged that a checklist could provide a potential complication if it is defined with ambiguous terms. Therefore, utilization of definitions of readiness levels with ambiguous terms to assess readiness should be addressed.

For readiness of the entire system, Sauser et al. developed a method for quantifying overall system readiness with their SRL metric. This method involves mathematically combining the TRL metric and IRL metric to form a single SRL measure. However, issues with this system have been acknowledged. First, it is acknowledged that the mathematical aggregation of TRL and IRL is a bad approach because they are formed with ordinal scales. Additionally, it is acknolwedged that this aggregation presumes an assumption of independence between TRL and IRL, which may not be true. [49, 46]

With respect to development difficulty, it was acknowledged that current readiness-specific metrics do not capture the expected difficulty of maturing a technology. However, capturing the expected difficulty of the development process can provide valuable insight for decision makers. It's important to establish the type of difficulty that should be quantified for each phase of development so that relevant difficulty information is available. There are three different types of difficulty that can be captured for the development process: the relative difficulty among different readiness levels, the relative difficulty among technologies trying to reach a given readiness level, and the difficulty of a performance objective or goal.

Relative difficulty among different readiness levels refers to the varying levels of inherent difficulty between different levels of readiness. For example, Mankins states that it is more difficulty to go from TRL 2 to TRL 3 than it is to go from TRL 6 to TRL 7. Relative difficulty among different technologies refers to the varying amount of difficulty that will be observed for a set of technologies that are under development. For example, if two technologies are trying to increase their readiness from TRL 4 to TRL 5, one technology may face a greater amount of difficulty in achieving TRL 5 than the other.

The last type of difficulty, the difficulty of a performance goal, is different than the previous two. It is not a difficulty measure that can be applied to a single technology.

Rather, it is a measure that captures the capabilities, or lack thereof, of all potential systems and technologies. It can be viewed as a measure of the *aggressiveness* of a given performance goal for the entire vehicle.

Two measures of difficulty were presented, R & D^3 and AD^2. The definition of R & D^3 may lead one to believe that it captures the first and second type of difficulty for a set group of technologies or alternatives because of the way it is stated (*How hard will it be to move from one TRL to the next for a given set of research and development objectives?*). However, the scale presented in Figure 15 for R & D^3 is more relevant for the third type of difficulty because it uses probability of success of meeting a stated goal as a measure of difficulty.

Recall, AD^2 attempts to capture *What is required to advance the immature technologies from their current TRL to a level that permits infusion into the program within cost, schedule, and risk constraints?*. Therefore, it is categorized as either the second type of difficulty or a combination of the first and second. The measure used to communicate AD^2 is a percentage of development risk, however no method for quantifying the risk was provided.

Based upon this discussion, the key observations are summarized as:

- Technology Readiness Level is the current state of the art for measuring and communicating technology readiness, but there have been some identified shortcomings in the literature

- Characteristics such as technology criticality and difficulty do not necessarily need to be captured by a measure of technology readiness

- The use of ambiguous terms to define each level of the TRL system is identified as the largest potential shortcoming when utilizing TRL for a measurement or communication device

- Integration readiness is an important aspect of system readiness and should be captured, if possible, at the technology level

- The mathematical combination of values from an ordinal scale (such as TRL) is not an accepted practice, therefore individual TRL values cannot be directly added to represent system readiness
- Different types of development difficulty exist, and the current difficulty metrics do not encompass all three types

2.2 Uncertainty and Probabilistic Analysis

Uncertainty is the state of being not definite or not completely known. Uncertainty exists in all aspects of life, including the disciplines of science and engineering. The ability to quantify and track uncertainty can assist in system risk analysis and provide decision makers with valuable trade-off information that would otherwise be unavailable or unknown. Therefore, it is important to follow well-defined, mathematically-based procedures for the identification, assessment, and treatment of uncertainty sources. The process of uncertainty quantification can be divided into five steps, as shown in Figure 19. These steps are: identify, characterize, propagate, analyze, and reduce. The proceeding sections will provide a thorough look at the current state-of-the-art of uncertainty quantification, including philosophies for uncertainty classification, strategies for uncertainty characterization and propagation, and methods for sensitivity analysis. Finally, the connection of uncertainty and technology development will be addressed.

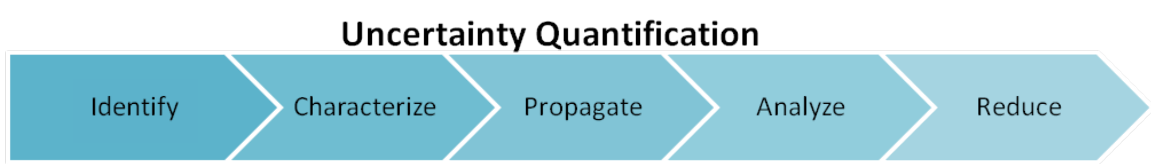

Figure 19: Uncertainty quantification process.

2.2.1 Uncertainty Classification

There are many sources of uncertainty in system design and development, and there is a need for a sound taxonomy to categorize the types according to the fundamental essence of the sources and how they affect the system[77]. In the literature there exists several different taxonomies used by different science and engineering disciplines. Robertson provides a thorough enumeration and comparison of several prevalent taxonomies in his Ph.D. dissertation[86]. Included in his work is a taxonomy used in the field of ecology[85], a taxonomy used in the field of civil engineering[13], a taxonomy used in the field of structural engineering[72], a taxonomy used in the field of systems engineering[6, 107], a taxonomy used in the field of modeling and simulation[76], a taxonomy used in the field of space architectures[114], and a taxonomy used in the field of complex system design[107]. Of these existing taxonomies, a closer look will be given to the ones from the fields of modeling and simulation and complex system design.

Figure 20 displays the taxonomy of uncertainty created by Oberkampf et al. for the discipline of modeling and simulation. In this taxonomy uncertainty is broken down into three main types: epistemic, aleatory, and error. Error is further broken down into unacknowledged error and acknowledged error. The terms epistemic uncertainty and aleatory uncertainty are very prevalent in the uncertainty community, and their definitions have generally been agreed upon. Aleatory uncertainty can be defined as the inherent, or natural, variation of a measured quantity[78, 77, 75, 118]. It is also referred to as irreducible uncertainty, inherent uncertainty, variability, stochastic uncertainty, random uncertainty, uncertainty due to chance, and Type A uncertainty[88, 108, 94, 77]. Epistemic uncertainty can be defined as uncertainty due to incomplete knowledge[77, 75, 78]. It is also referred to as reducible uncertainty, knowledge uncertainty, subjective uncertainty, Type B, and cognitive uncertainty[88, 93, 108, 77, 118].

Oberkampf et al. agree with these definitions for aleatory and epistempic uncertainty[76]; however, the uncertainty taxonomy provided for modeling and simulation is unique because the authors distinguish error from the other two categories. Under this taxonomy error is defined as "a recognizable inaccuracy in any phase or activity of modeling and simulation that is not due to lack of knowledge." Acknowledged errors are described as errors where their relative impact is well recognized. Likewise, unacknowledged errors are described as errors which are not recognizable.

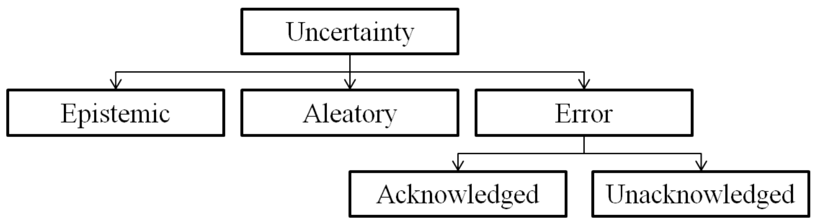

Figure 20: Uncertainty taxonomy for modeling and simulation [76].

Figure 21 provides a depiction of the taxonomy of uncertainty created for complex system design by Thunnissen in his PhD dissertation. In this taxonomy, there are four main types of uncertainty: ambiguity, epistemic, aleatory, and interaction. Ambiguity can also be defined as vagueness or imprecision and can be reduced through creating concrete definitions and clear language[86]. Interaction uncertainty is defined as uncertainty due to potential unanticipated interactions of events, systems, and disciplines. In this taxonomy, aleatory is specifically defined as "the inherent variation associated with a physical system or environment". This definition agrees with the previously provided definition for aleatory uncertainty.

Thunnissen's uncertainty taxonomy divides epistemic uncertainty into three main sub-categories: model, phenomenological, and behavioral. Model uncertainty, or more commonly known as model form uncertainty, is defined as "the accuracy of a mathematical model to describe an actual physical system of interest"[107], and is due to lack of knowledge about the precise model to represent the phenomena of interest[88].

The term model form uncertainty is used to capture all sources of uncertainty related to the model, including all assumptions, conceptualizations, abstractions, approximations, and mathematical formulations on which the model relies[77]. Thunnissen formally breaks model uncertainty into three types: approximation errors, programming errors, and numerical errors. Approximation errors results from any simplifying assumptions that are made to reduce the complexity of the system being modeled. Programming errors result from mistakes made when the model is under development. Numerical errors result from discritization, convergence criteria thresholds, and rounding-off of numbers[88].

The second type of epistemic uncertainty is phenomenological uncertainty. Phenomenological uncertainties are sometimes referred to as "unknown unknowns"[86, 107]. They are sometimes referred to unimaginable phenomenon which can cause failures or undesired results[86, 72]. This type of uncertainty is important when the state of the art is being advanced[107, 72]. The final category of epistemic uncertainty is behavioral uncertainty, which refers to uncertainties resulting from actions of individuals. Behavioral uncertainty is divided into design, requirement, volitional, and human errors. Design uncertainty results from a non-fixed design, which occurs early during the design process. Requirements uncertainty results from non-fixed requirements, or goals, for the system under development. Volitional uncertainty is due to unknown decisions that will be made in the future by program management. Lastly, human errors are mistakes made by any individual associated with the program.

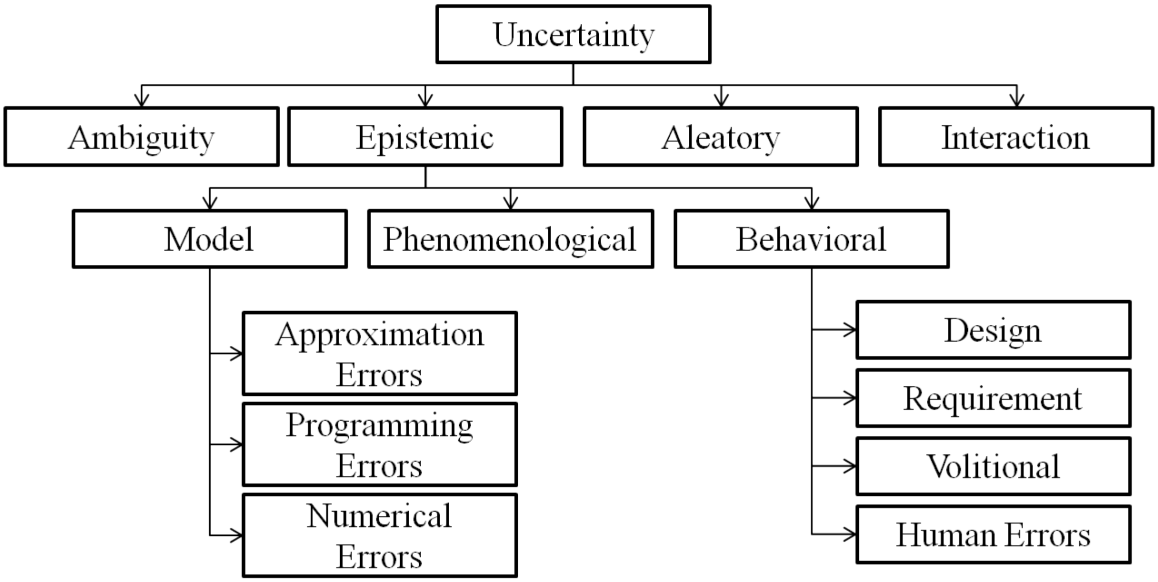

Figure 21: Uncertainty taxonomy for complex system design [107].

2.2.2 Uncertainty Characterization

Once uncertainty sources have been identified they can be characterized. Characterization refers to determining how to mathematically represent the uncertainty sources. The literature presents many different methods for the representation of uncertainty sources, such as interval analysis, evidence theory, possibility theory, and probability theory[41]. In the risk assessment community, probability theory is the most prevalent representation method[88]. The specific type of representation within probability theory utilized depends on the characteristics of the uncertainty source and the philosophy of probability theory followed. The following subsection will provide a brief background on probability theory and the two separate philosophies that can be followed, objective and subjective.

2.2.2.1 Probability Theory

Probability theory is well-established and its origins can be traced to mathematicians, such as Pascal, Leibniz, Fermat, and Bernoulli[113]. As the capabilities of probability theory have grown it has been utilized by many disciplines, including aerospace system design. There are two main views, or philosophies, of probability theory: objective (frequentist) and subjective (Bayesian). The basic principles of probability theory will be provided, as well as explanations of both views.

Probability theory is the branch of mathematics that deals with quantities having random distributions. These quantities are referred to as random variables. For example, experiments generate data sets that are subject to uncertainty, meaning the data sets generated by identical experiments will not necessarily be identical. Therefore, the data can be represented by a random variable and its possible outcomes can be explained with probability theory.

The set of all possible outcomes of an experiment is defined as the sample space Ω, and an event can be defined as a subset of the sample space. Given two events, A and B, their intersection is denoted as $A \cap B$ and their union is denoted as $A \cup B$. If two events are mutually exclusive, $A \cap B = \phi$. If the sample space Ω contains a finite number of elements E_i, every element within Ω has a probability value $f(x)$, which is known as its probability mass function (PMF). Extending this, the probability of an event A is equal to the summation of the probability values of all elements within A.

Formalized definitions of the basic rules of probability theory are known as the axioms of probability theory. The axioms are as follows[19]:

1. $O \leq P(E_i) \leq 1$
2. $P(\Omega) = 1$
3. Additive: $P(\cup_{i=1}^{n} E_i) = \sum_{i=1}^{n} P(E_i)$ for $n = 1, 2...N$ where $E_1, E_2, ...$ are mutually exclusive

Application of the axioms to finite, countable sample spaces is straightforward, but the concepts can also be extended to continuous, uncountable spaces. In continuous spaces probability is commonly defined in terms of a cumulative density function

(CDF) and a probability density function (PDF). The PDF, $f(x)$, of a random variable X defined over the set of real numbers R has the following characteristics [113] :

1. $f(x) \geq 0$, for all $x \in R$
2. $\int_{-\infty}^{\infty} f(x)dx = 1$
3. $P(a < X < b) = \int_{a}^{b} f(x)dx$

The CDF of of a random variable X, $F_X(x)$, is defined as:

$$F_X(x) = P(X \leq x) = \int_{-\infty}^{x} f(t)dt, for - \infty < x < \infty \tag{6}$$

Conversely, when $F_X(x)$ is perfectly continuous and differentiable, the relationship between the CDF and PDF is:

$$f_X(x) = \frac{dF_X(x)}{dx} \tag{7}$$

PDFs of two random variables X and Y can also be given as a joint PDF, $f(x, y)$, which and has the following properties:

1. $f(x, y) \geq 0$, for all (x, y)
2. $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y)dxdy = 1$
3. $P[(X, Y) \in A] = \int \int_{A} f(x, y)dxdy$, for any region A in the xy plane

Given the joint PDF of two variables, the marginal distributions of each, $f_X(x)$ and $f_Y(y)$ can be found by integrating over the domain of the opposite variable. For example, to find the marginal distribution of the variable X, $f_X(x)$, simply integrate the joint PDF $f(x, y)$ over the entire domain of Y. The marginal and joint PDFs of X and Y are used together to form conditional distributions, which produce conditional probabilities. The conditional probability $P(A|B)$ is interpreted as the probability of event A given event B and is calculated as shown :

$$P(A|B) = \frac{P(A \cup B)}{P(B)} \tag{8}$$

The concept of conditional probability, shown in Equation 8, helps form Bayes theorem, which is the backbone of the Bayesian methodology. Equation (8) can be rearranged and written as:

$$P(A \cap B) = P(A|B)P(B) \tag{9}$$

Likewise, the equation for the probability of B given A, $P(B|A)$, can be rearranged and written as:

$$P(A \cap B) = P(B|A)P(A) \tag{10}$$

Setting the right side of Equation (9) equal to the right side of Equation (10) and rearranging results in Bayes Theorem, which is displayed in (11).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{11}$$

This form of Bayes theorem is utilized widely in the Bayesian methodology. A complete description of the Bayesian methodology will be provided later.

2.2.2.2 Objective and Subjective Interpretations

The classical, or objective, interpretation of probability is based upon the notion of equally likely outcomes[116]. This view of probability theory was originally developed in the context of games of chance, where the probability of an event is equal to the number of outcomes comprising that event divided by the total number of possible outcomes. The concept of games of chance can be extended to encompass any scenario or event where multiple repeated trials are being performed, such as experimentation[19]. Commonly, this interpretation is labeled the frequentist view and the probabilities are referred to as physical probabilities.

There are various random variable models, such as the normal distribution or the uniform distribution. The PDF of each random variable model is defined as a function of a parameter or set of parameters, which is represented by the vector $\boldsymbol{\theta}$. In the context of the frequentist view, the parameters $\boldsymbol{\theta}$ are said to be deterministic. Estimating the deterministic values of the parameters becomes the objective when trying to determine the model, and the uncertainty of the actual value of the parameters is represented via confidence intervals. Confidence intervals represent the variability due to inherent randomness.

The objective interpretation of probability theory is straightforward and intuitive, but its applicability is limited by the restriction to equally likely outcomes.[116] When the phenomenon of interest cannot be, or has not been, repeatedly measured, the objective interpretation cannot be utilized. In these situations a differing interpretation of probability theory can be utilized, the subjective interpretation.

Under the subjective view of probability theory the term probability is interpreted as the degree of belief [19]. In this context, subjective probability values can be assigned to any entity without the occurrence of random experimentation. Therefore, the subjective probability values do not refer to anything that has necessarily been "observed", and are not deemed physical probabilities. Subjective probabilities are used within the Bayesian methodology and sometimes referred to as Bayesian probabilities.

Unlike the objective interpretation, the parameters defining a probability distribution can be represented by their own probability distributions. In this context, the distribution of the deterministic entity represents the complete lack of knowledge of the actual value. As knowledge of the entity increases the distribution will converge, in theory, to the deterministic value. Additionally, manipulation of subjective probabilities with the mathematical rules of probability previously provided is not transparent but can be shown to follow from an underlying axiomatic framework[116].

2.2.2.3 Aleatory and Epistemic Characterization

In the literature it is agreed upon that purely aleatory uncertainty sources should be characterized by probability density function (PDF) with deterministic, scalar model parameters[88]. Therefore, aleatory uncertainty representation strictly follows the objective view of probability theory. For purely epistemic sources of uncertainty, there is no single clear approach. The literature shows there is a divide in the uncertainty community on how epistemic uncertainty sources should be properly characterized. The difference in opinion stems from the differences in the two interpretations of probability theory.

If the objective probability view is followed, episteimc uncertainty sources are characterized as an interval with no likelihood associated with any value in the interval[88]. Only aleatory uncertainty sources, whose PDF may be constructed from their observed variability, may be modeled as random variables with associated PDFs[75]. One common misconception is that 'an interval with no likelihood associated with any value' is equivalent to a uniform distribution; however, a uniform distribution assumes an equal likelihood for all of the values within the interval.

In contrast, Bayesian probability theory allows for epistemic uncertainty sources to be represented by probability functions. In this context the assigned PDF represents the degree of belief of the value for the uncertain entity, and it is not associated with actual counted outcomes. Utilization of Bayesian probability theory enables the combination the affects of aleatory uncertainty and epistemic uncertainty[75, 78].

2.2.2.4 Uncertainty Elicitation

The definition of probability distributions, or intervals, for uncertainty sources is primarily done in two ways, through data reduction or expert elicitation. When a sufficient amjount of observed data exists for an uncertain quantity it can be used to determine the quantity's variability. First, a specific random variable model is chosen, such as random, normal, Beta, etc. Selection of the appropriate random variable model is done according to observed characteristics of the collected data, the context surrounding the quantity of interest, previous knowledge of the quantity, or expert opinion [39, 40].

Next, the parameters of the model are defined using a parameter estimation method. One such method commonly used is maximum likelihood estimation(MLE). A random variable y_i is a function of the the measured quantities of y_i and the model parameters, represented by θ, as shown in Equation (12). The number of model parameters to be estimated depends on the random variable model chosen. For example a Normal distribution is a function of two model parameters, σ and μ, and a Beta distribution is a function of two different model parameters, β and α. Equation (13) displays the probability density function for the normal distribution.

$$y_i \sim f(\theta, y_i) \tag{12}$$

$$y_i = \frac{1}{\sqrt{2\pi\sigma^2}\exp^{-\frac{(y_i-\mu_i)^2}{e\sigma^2}}} \tag{13}$$

Recalling Bayes theorem from Equation (11), it can be re-written in terms of the random variable and its model parameters as shown in Equation (14). In this equation, the denominator $P(y)$ is solely a function of the measured data and can be ignored since the conditional densities will be computed for the same data set. In Equation 14 $\frac{1}{P(y)}$ is referred to as the constant of proportionality, $P(\theta)$ is referred to as the prior density of θ, $P(y|\theta)$ is the likelihood, and $P(\theta|y)$ is the posterior density of θ.

$$P(\theta|y) = \frac{P(y|\theta)P(\theta)}{P(y)} \tag{14}$$

When parameter estimation is taking place the prior distribution for θ, $P(\theta)$, is fixed. Therefore, Equation (14) can be rewritten as:

$$P(\theta|y) = P(y|\theta)k(y) = \mathcal{L}(\theta|y) \tag{15}$$

where $k(y) = \frac{P(\theta)}{P(y)}$ is an unknown function of the data that can be treated as a constant. This equation is known as the likelihood, $mathcalL$, and is proportional to the probability of observing the data when the parameters of the distribution are treated as variables and the data is fixed.

When conducting MLE, the best parameters for the random variable distribution are the set $\hat{\theta}$ that maximize the likelihood function in Equation (15). The first step in calculating this is re-writing the likelihood of the entire sample as a function of the individual likelihoods of all observations. This is represented in Equation (16). It is important to point out that a key assumption made in this process is that all observations are independent of each other.

$$\mathcal{L} = \prod_{i=1}^{N} \mathcal{L}_i = \prod_{i=1}^{N} P(y_i|\hat{\theta}) \tag{16}$$

Simplification of Equation 16 is made by taking the natural logarithm, which transforms the equation from a series of products to a summation. The natural logarithm transformation is shown in Equation (17). This is the final form of the likelihood equation that is used in the MLE process. The final step is to set Equation (17) equal to zero, and solve for the estimated parameters, $\hat{\theta}$.

$$\ln \mathcal{L} = \sum_{i=1}^{N} \ln P(y_i|\hat{\theta}) \tag{17}$$

For scenarios where there is not enough data, or there is no relevant data, to sufficiently estimate a probability function, subject matter experts (SME) can be utilized to develop subjective probability distributions. SMEs can be utilized in many different ways to develop a probabilistic representation of a random variable. It was previously mentioned that expert elicitation could be used to determine the proper probability model that should be used. Additionally, SMEs could be used to estimate the individual parameters that define the selected probability distribution model or to provide bounds on the values of the entity under consideration. The amount of insight an SME can provide depends on their knowledge of the physics of the project and the specific scenario being assessed.

Kirby et al. demonstrated a method that utilizes SME elicitation to form a Beta distribution that represents the expected impact of a developing technology[58]. The method they used was taken from Batson and Love, and it involves transforming information regarding the minimum, maximum, and most likely value of an entity into the parameters that define a Beta distribution.[14] In addition to the value estimates, confidence measures are also solicited from the experts. The confidence scale has five associated levels and the experts must select one level each for the maximum value, minimum value, and most likely value. Therefore, a total of six values were solicited from the experts to form the Beta distributions for each technology under consideration.

It is important to note that the use of SMEs to form subjective probability distributions that will then be manipulated using probability theory is not accepted by all in the uncertainty community. The first reason it is not accepted is due to the very nature of subjective probabilities, which was mentioned in a previous subsection. The second reason is that different people can have different probabilities for the same event.[116] Therefore, it may be necessary to solicit information from multiple experts in a given field to gather adequate information about an uncertain entity.

2.2.3 Uncertainty Propagation

Uncertainty propagation is the process of mathematically mapping sources of uncertainty, from wherever they originate, to the uncertainties in the simulation results[77]. Therefore, if outputs are a function of uncertain inputs, they too will be uncertain and will have a corresponding probability function associated with them. There are many different ways to perform uncertainty propagation, and one such category of methods is sampling methods. Generically speaking, when sampling methods are utilized the process of uncertainty propagation is to sample the inputs, run the simulation, and repeat until enough simulation results are gathered to adequately characterize the output probability distributions.

Many sampling techniques exist in the literature, and the chosen technique depends on the complexity of your model and the amount of time it takes to execute your simulation. A simple sampling technique can be created in the form of a random number generator, where a random number is generated for each uncertain input and then transformed into a relevant value for the corresponding input. In this context, no consideration of the input distribution is given other than values that bound the input.

Another sampling technique that is commonly used in probabilistic aircraft design is Monte Carlo simulation.[28, 27, 58, 45, 80] A Monte Carlo analysis can be used to characterize the probability distribution, in either PDF or CDF form, of the objective function. Monte Carlo analysis is a sampling based uncertainty propagation approach where the inputs are sampled based upon their previously defined probability distributions. The resulting samples create a set of input vectors which are used to perform simulations of the analysis code. The resulting outputs of the analysis code for each input vector are used to form the output distribution. This process is illustrated in Figure 22. [28]

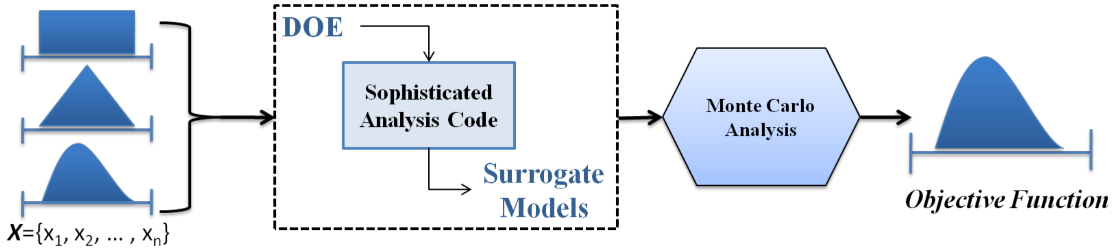

Figure 22: Monte Carlo uncertainty propagation method.

As the number of probabilistic inputs increase, the number of samples required to form the output distribution increase. This may lead to issues with computational effort, and simplifications may need to be made. One such simplification suggested by Delaurentis is the creation of surrogate models, or approximation models, for the analysis code to reduce the complexity and computational effort required.

Surrogate models, or metamodels, are approximations of a complex analysis model [70, 107]. Hence, they can be described as a model of a model [107]. Surrogate models are based upon the original models, therefore the physics-based relationships between the inputs and outputs will be retained. They are, however, less complex than the original analysis model but still accurate to a certain degree. The reduced complexity can lead to faster simulation times and less computational expense.

There are many different types of surrogate models, including Response Surface Equations (RSEs) and Artificial Neural Networks[70, 61]. RSEs are polynomial regressions of the model outputs as a function of the model inputs. They are developed by using a Design of Experiment (DOE) technique to sample the inputs within their valid ranges and then regressing the simulation outputs as a function of the inputs. The ability of the RSE to capture interactions of the input variables depends on the order of the model. For example, a quadratic regression model, or second order RSE, will capture linear effects, quadratic effects, and two-variable interactions[61].

Artificial Neural Networks (ANN), another type of surrogate model, are models that are inspired by the central nervous system and used heavily in the discipline of machine learning. ANNs map inputs to outputs by developing a network of hidden nodes, or neurons, which mimics a biological neural network. There can be many layers of hidden nodes, and the number of layers depends on the complexity of the phenomena being modeled. Determination of the nodes, and their weightings, is done by utilizing a set of training data. In general, ANNs provide a better representation of systems with non-linear behavior than RSEs.

2.2.4 Measures of Uncertainty

Communication of the amount of uncertainty that surrounds a quantity is important when one desires to make comparisons among a group of uncertain quantities. Representing the amount of uncertainty that exists in a distribution for the purpose of comparing distributions with scalar values has been done by the use of various measures in the literature.[91] Many measures exist and there is no general consensus on a single measure of uncertainty that should be used to quantify shrinking uncertainty and provide comparisons among technology sets.

The simplest measure, or statistic, that can be calculated from a probability distribution is the expected value, or mean. The expected value is a measure of the central tendency of a random variable; it is not the most likely value of a random variable. Equation (18) represents the formula for calculating the expected value, where X is the random variable under consideration, x is a realization of X, and $f(x)$ is the PDF of X.

$$\mu = \mathbb{E}\left[X\right] = \int_{\mathbb{R}} f(x)dx \tag{18}$$

The expected value is a simple statistic that is good for representing and comparing the central tendencies of distributions, but it does not provide a measure to compare the spread of the distributions. The most common measure used to represent the spread of a distribution is the variance. The variance of a random variable is the second central moment and it's formula is defined in Equation (19). When distributions are similar (i.e. same model type and same mean), variance is commonly used to compare the amount of existing uncertainty. In these cases, larger values of variance directly corresponds to more existing uncertainty.

$$\sigma^2 = Var(X) = \mathbb{E}\left[(X - \mu)^2\right] \tag{19}$$

The use of scalar measures like mean and variance to summarize the uncertainty surrounding a quantity is common, but Saltelli argues that they do not provide a good summary of subjective uncertainties for two reasons. The first part of their argument is information is lost when only mean and variance are used to communicate uncertainty. The second part of their argument is means and variances are not natural quantities for summarizing subjective uncertainty. Instead, they suggest the use of quantiles associated with a probability distribution or information taken from a CDF[91].

The use of quantiles or a CDF provide a glimpse of how much uncertainty exists and what the uncertainty actually looks like. When analyzing uncertainty surrounding an objective function, or any quantity that has a stated goal value, the CDF can be used to calculate the probability of success (POS) of meeting the goal. The POS can then be used as a scalar quantity to communicate and compare uncertainty. The equation for POS depends on the direction of improvement of the objective function. Equation (20) provides the equation for POS for goals where you are trying minimize below a given goal or maximize above a given goal.

$$POS = \begin{cases} F(X), & \text{if minimizing} \\ 1 - F(X), & \text{if maximizing} \end{cases} \tag{20}$$

Another measure found in the literature that aids in representing the shape of the uncertainty distribution is the tail conditional expectation (TCE). The TCE is the expected value of the portion of the probability distribution that is above or below a specified value. The equation for TCE below a specified value is presented in Equation (21):

$$TCE = \mathbb{E}\left[X|X \leq x^{\alpha}\right] \tag{21}$$

where

$$x^{\alpha} = inf\{x \in \mathbb{R} : P(X \leq x) > \propto\} \tag{22}$$

2.2.5 Sensitivity Analysis

It is often desired to conduct assessments on the effects uncertain inputs have on outputs. Decision makers may need to determine the value of reducing certain sources of uncertainty over others, and further, determine what type of information is needed to provide that value[105]. One such analysis that is commonly conducted on uncertainty quantification results is sensitivity analysis. Sensitivity analysis (SA) is the process of determining how the simulation outputs depend on all of the factors that the model is composed of[77]. Specifically, the goal of SA is to apportion the uncertainty in a given output to the uncertainty in each of the inputs[93].

SA is considered an integral part of model development and is used to increase the confidence in the model and its predictions by characterizing how the model outputs respond to changes in the model inputs[91]. It was first developed to assess uncertainties associated with input variables and model parameters, but is now utilized to characterize the effects of all sources of uncertainty represented in a model. SA provides model developers with the ability to determine if a model resembles the system it represents, the factors that contribute to the output variability the most, parts of the model that are insignificant, optimal regions within the simulation space, and interactions among factors[91, 105].

There are various levels of SAs, and they can be grouped as either screening methods, local SA(LSA) methods, and global SA(GSA) methods. Screening assessments utilize low computational effort to identify the subset of inputs that control the majority of the output variability[91]. The results of screening assessments are typically qualitative rankings of input variables with respect to their comparative levels of importance. To obtain higher fidelity results, a LSA or GSA required.

LSAs quantify the local impact of inputs on the model and are conducted through calculations of partial derivatives of the model outputs with respect to the model inputs. The assessments are deemed local because the quantified impact of one input is calculated while holding all others constant at some nominal baseline value. The derivatives are calculated by allowing the inputs to vary a small amount around the nominal value. Therefore, local SAs are only practical when the variation of an input around the baseline is small and the model is linear.

GSAs incorporate the influence of the range and shape of inputs. Unlike LSAs, GSAs do not assume fixed values for other inputs while assessing the effect of one uncertain input; the amount the other inputs are incorporated depends on the order of the effects being considered. First order effects calculated from a GSA calculate the effect of the uncertainty of one input when the other uncertain input quantities are averaged. Second order effects capture the interactions of two variables, which are calculated with the first order effects of the two factors. Third order effects, consider three-variable interactions, etc. Altogether, there are a total of $2^n - 1$ possible effects that can be calculated, where n is the total number of uncertain inputs. A common GSA technique is the Analysis of Variance(ANOVA).

The selection of what SA to conduct depends on the objectives of the assessment, the amount of computational effort that can be afforded, and the complexity of the system model. Sometimes it is possible to use a lower fidelity analysis first and utilize its result to facilitate a higher fidelity analysis. For example, LSA or GSA is desired but the model complexity makes the required computational effort too high, screening methods can be used to simplify the model, and then a LSA or GSA can be completed.

Once a SA has been conducted, the factors under consideration can be ranked according to their impact on the response metric. There exists multiple sensitivity measures that can be used to facilitate this ranking. Examples of such metrics found in the literature are the sensitivity index, importance measure, and first order effect. Again, the selection of the sensitivity measure depends on the purpose of the sensitivity analysis and the type of SA utilized.

2.2.6 Uncertainty Quantification Observations

This chapter presented a thorough investigation of uncertainty quantification and the link between the topic of uncertainty and the topic of readiness. It was observed that the propagation of low-level uncertainty to system level metrics can be facilitated by combining the abilities of a modeling and simulation environment with sampling techniques and computational reduction methods like surrogate modeling. Furthermore, several metrics were presented that aim to capture probabilistic information that results from uncertainty propagation. The metrics attempt to summarize probability distributions, however it was established that there is no general consensus about which represents the distribution the best.

It was also observed that probabilistic results can be used to aid further analysis, such as sensitivity analysis. Sensitivity analysis was established as an important tool that can be used on probabilistic information to identify sources of uncertainty that are driving the overall variation in the responses of interest. The information resulting from sensitivity analyses can be used for identification or prioritization of alternatives. Finally, it was observed that a well-defined uncertainty taxonomy is necessary to enable the selection of an appropriate uncertainty analysis plan. Many taxonomy's exist in the literature, but the separation of aleatory and epistemic uncertainty is prevalent in most.

The relevance of the identified uncertainty metrics and analysis methods will be further discussed in Chapter Three. However, before uncertainty analysis is considered, it is important to define an uncertainty taxonomy that will be utilized within this research. An uncertainty taxonomy for this research was specifically crafted based upon the previously presented uncertainty taxonomies found in the literature and can be seen in Figure 23. The taxonomy presented by Thunnissen varies widely from the taxonomy provided by Oberkampf et al., mostly due to the amount of detail, or number of sub-categories, Thunnissen provided. However, one thing that remains constant in both is the separation of aleatory uncertainties and epistemic uncertainties. The use of aleatory and epistemic has been deemed by many as desirable because it is a workable and effective uncertainty scheme[88, 118, 77]. Therefore, the uncertainty taxonomy created for this research has only two main categories of uncertainty, aleatory and epistemic.

The benefits of using the aleatory and epistemic uncertainty classifications include improved interpretation of uncertain information by analysts and decision makers. Distinguishing sources of uncertainty as either aleatory or epistemic enables the implementation of improved uncertainty analysis strategies. For example, separation of aleatory sources from epistemic sources enables engineers to focus their efforts strictly on gaining information that will reduce the epistemic sources[77].

The concept of characterizing uncertainties as either reducible or irreducible will be important during the experimentation planning phase of technology development, which is one reason why the separation of uncertainty sources as either aleatory or epistemic was deemed desirable. In this context, aleatory uncertainty is considered irreducible and the definition of is consistent with the definition previously presented, which is the inherent or natural variation of a measured quantity[77, 118, 75, 78]. Likewise, the definition utilized for epistemic uncertainty also follows the previously presented definition, which is uncertainty due to incomplete knowledge[77, 75, 78].

Epistemic uncertainty is considered reducible because it can be reduced and potentially eliminated with an increased state of knowledge [118].

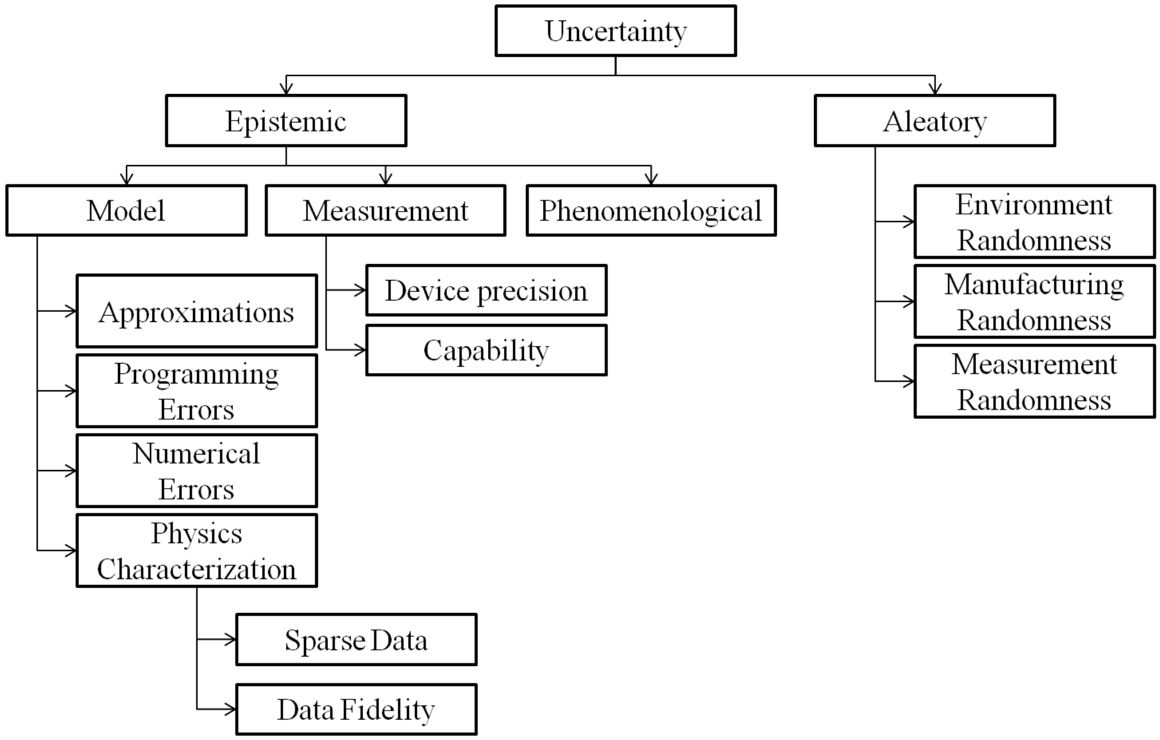

Figure 23: Uncertainty taxonomy utilized for this research

Sources of aleatory uncertainty cannot be reduced but they can be controlled. Therefore, engineers attempt to quantify the impact of aleatory uncertainty on a system or a risk analysis, but do not plan actions to reduce them. For this taxonomy, aleatory uncertainty is divided into three types: environment randomness, manufacturing randomness, and measurement randomness. *Environment randomness* is any factor in the operational or testing environment that is uncontrollable to the the scientist or engineer. An example of this is the expected weather in an aircraft operating environment. *Manufacturing randomness* is defined as any manufacturing factor that is out of the control of the design engineer, such as undetected manufacturing defects or slight variations in manufactured systems that have the same design. The last type of aleatory uncertainty, *measurement randomness*, is the inherent randomness that occurs when measuring a given quantity. Engineers can attempt to quantify measurement randomness by conducting repetitions or taking repeated measurements.

Epistemic uncertainty is divided into three main categories: model uncertainty, measurement uncertainty, and phenomenological uncertainty. *Model uncertainty* is defined as the uncertainty, or error, present in all mathematical models that attempt to represent a physical system. Model uncertainty is divided into approximations, programming errors, numerical errors, and physics characterization. The development of a mathematical model to represent complex phenomena requires assumptions and simplifications to be made. This includes simplifying assumptions concerning the anticipated operating environment of the modeled system and simplifying assumptions concerning the anticipated operating scenario [88]. These uncertainties are categorized under *approximations* and are epistemic sources of uncertainty because more fidelity could be built into the model if the resources were available[93]. An example of an uncertainty source that would be categorized as an *approximation* would be any uncertainty added into the analysis through the use of surrogate models.

The definition for *programming errors* is consistent with the previously presented definition, which is any error or blunder in the model that results from human error. *Numerical errors* refer to any mathematical approximations or limitations that affect the assessment. For example, rounding and discretization could both affect the output of an analysis. The final category of model uncertainty is *physics characterization*. This category is where the lack of understanding of the phenomena under investigation materializes. Selection of the appropriate type of mathematical model, such as linear versus exponential, and the selection of the parameters that define the chosen model are large contributors to the overall model form uncertainty. The ability to select the most appropriate model may be difficult due to the amount, or lack, of available data. Lack of appropriate data may mean there is only a limited number of point data available[94], or in the case of large system models, there is no existing data[88]. This type of uncertainty will play a key role in the approach proposed for experimentation planning that will be presented in a later chapter.

Another main type of epistemic uncertainty, *measurement uncertainty*, is divided into device precision and measurement capability. *Device precision* refers specifically to the fidelity of the measurement device, i.e. the number of significant digits the device can capture. *Measurement capability* refers to the capabilities of the measurement devices utilized to capture the phenomena under investigation. Examples of such uncertainty sources are when the response of interest is not able to be directly directly measured due to an obstruction or obstacle. The final type of uncertainty included in the taxonomy is *phenomenological uncertainty*, and its definition follows the previously provided definition of "unknown unknowns." It is important to include phenomenological uncertainty in this taxonomy because the development of new technologies deals extending the current state of the art.

CHAPTER III

METHODOLOGY FORMULATION

In Chapter Two it was acknowledged that the methodology developed within this research will address a series of key questions that have been identified for each phase of technology development. Figure 11 provided an enumeration of the steps that included in the methodology and the identification of alternatives, value metrics, and required analysis procedures for each relevant step in the process must be further addressed. Furthermore, in Chapter Two it was acknowledged that the existing TIES methodology can be leveraged as a baseline for the methodology and it can be augmented with the inclusion of uncertainty quantification techniques to form a methodology that meets the defined research objective. Figure 24 provides a depiction of where the steps of the uncertainty quantification process and the TIES methodology are realized in the resulting methodology, which is deemed the **Quant**itative **U**ncertainty **M**odeling, **M**anagement, and **M**itigation methodology, or **QuantUM**^{3} methodology.

As Figure 24 demonstrates, aspects of the TIES methodology fall within the first part of the QuantUM^3 methodology where the system architecture and technologies are selected. The QuantUM^3 methodology expands upon the TIES methodology to include the third and fourth phases of technology development where experimentation is planned and technologies are assessed for their transition readiness. The analysis procedures within each step of the QuantUM^3 methodology incorporates uncertainty quantification techniques as well as technology readiness assessments. The background information discussed in Chapter Two provides a benchmark for readiness assessments and probabilistic analysis. This information is used to further define the methodology through formal research questions and their corresponding hypotheses. The research questions focus specifically on how the supporting techniques are integrated to facilitate alternative identification, select metrics, and calculate the metric values. The resulting hypotheses provide an outline of each step within the QuantUM^3 methodology in order to address the overall research objective of this thesis.

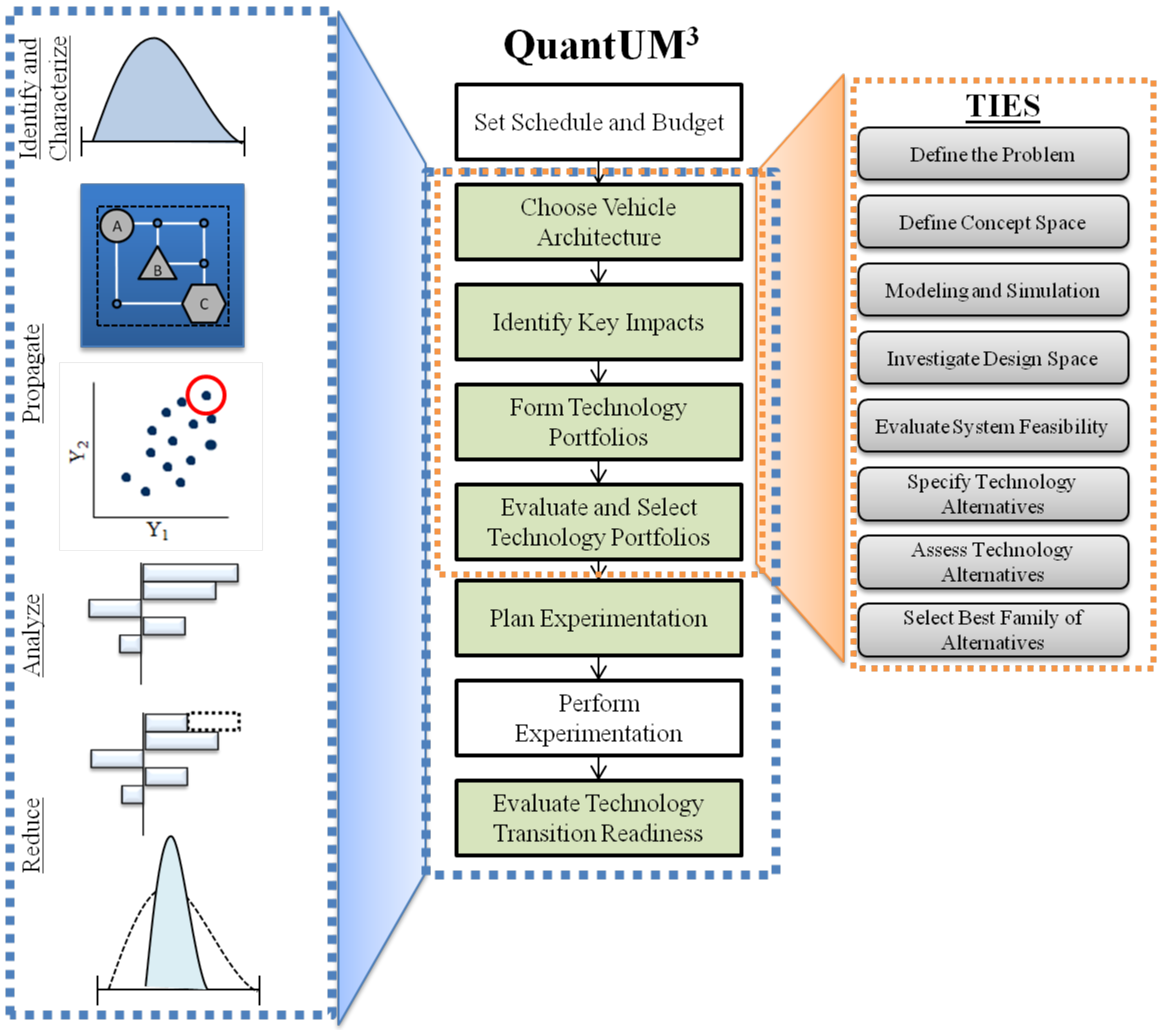

Figure 24: Depiction of how the QuantUM^3 methodology incorporates the TIES methodology and the uncertainty quantification process.

3.1 Strategic Planning Formulation

The first phase of development to be addressed is *Strategic Planning*. This phase addresses the following key questions:

- What is the system architecture?
- What are the system objectives?
- What are the important metrics for the given objectives?
- What capabilities/impacts are needed to meet the given objectives?

The first required prioritization is among the candidate system architectures. The term architecture refers to the description of the entities within a system, either physically or functionally.[26, 90] The terms *technology* and *system* have previously been defined and distinguished from each other, but the terms *technology* and *architecture* must also be delineated to determine the difference in architecture selection and technology selection. Based upon the previously provided definition, a technology is an entity that is integrated into an existing system at the sub-system or component level. Building upon this, it is established that trades involving an entire sub-system or multiple sub-systems, are referred to as architecture trades. For example, the term architecture could refer to the overall aircraft configuration (i.e. tube and wing versus hybrid wing body), engine architecture (i.e. direct drive versus open rotor), etc. Different system architectures are defined by enumerating the different choices for each of the sub-systems and then identifying compatible combinations.

Candidate architectures can be identified by investigating what industry partners have under development. For a technology development program, a relevant architectures would then be those that are considered to be viable and operational within the technology development program's intended timeline. Once the set of relevant architectures has been identified, they must be analyzed to produce the information used to facilitate down-selection. Architectures are selected for a variety of reasons, but this research focuses on decisions made based upon readiness and performance information. It is assumed architectures are identified based upon their readiness, so only performance assessments will be addressed. Therefore, the first research question to be addressed is:

Research Question 1.1: How should system architectures be analyzed to facilitate performance comparisons?

It was previously acknowledged that modeling environments enable performance assessments of systems that may not yet exist by capturing the relevant design variables and their relationships to the objective metrics. Therefore, if the objective metrics have been identified a relevant modeling environment could be built or identified. For this research, it is assumed that the objective metrics have been provided and the relationships between the relevant design variables and the metrics is well-established. This implies that the performance of each architecture can be assessed if an appropriate model is available and architecture design can be adequately represented.

When architectures are operational or well-established, such as a derivative aircraft design, the performance of the system for a given set of design parameters is characterized with deterministic values. Performance comparisons of different architecture designs would then be comparisons of point designs and no probabilistic analysis would be required. Within the TIES methodology, a design space exploration is conducted around a single system architecture. Therefore, the resulting performance analysis from the design space exploration is a set of deterministic performance assessments. The baseline architecture is then selected based upon the deterministic performance.

The results of a deterministic, design space exploration do not represent the future potential of the system architecture alternatives. When incremental improvements to a system are simulated, such as improvements that result from technology infusion, performance assessments then reflect a potential future system. When this information is available for the system architecture alternatives, decision makers would then be provided with more information about the potential performance of future aircraft systems to base their architecture selection decisions on. Based upon this observation, the following hypothesis was formulated:

Hypothesis 1.1: *Probabilistic analyses that represent the potential future performance of all candidate system architectures after technology infusion will provide the necessary information to facilitate architecture down-selection.*

The next key decision that must be addressed is selecting appropriate goals for the development program. For this research it is assumed an overall budget and schedule for the technology development program has been established. Therefore, the only goals left to address are the final readiness of the technologies and the performance goals. For readiness, literature shows that technology development is usually conducted until a technology reaches a TRL of 6 or 7. Therefore, this research assumes that is the goal readiness for reach technology under development. For performance, it was previously stated that it is assumed the system objective metrics are provided. However, the values for the metrics must still be determined.

The selected goal values are dependent on the expected performance of the selected architecture and the risk attitude of the decision makers. Decision makers can be risk averse, risk neutral, or risk seeking[9]. If the decision makers are risk averse, they are likely to set goals that are only small incremental improvements from the current state of the art. In contrast, aggressive performance goals would be set if decision makers are more inclined to accept high risk situations. Therefore, as long as decision makers are provided with information on the current performance of the selected architecture and its potential future performance, performance goals for the technology development program can be set.

Once the goals have been set, they can now be further decomposed to aid further planning for the development program. This leads to the next two research questions:

Research Question 1.2: How can important measures that drive the performance objectives be identified?

Research Question 1.3: How can all sets of required system impacts that enable the performance objectives to be met be identified?

Systems are composed of various sub-systems and components that provide the system different capabilities. Metrics measuring important aspects of each piece of the system can be connected in a hierarchy to demonstrate how information flows from the bottom level to the top level. When a system is complex a high level metric can be a function of a large number of lower level metrics. Without a modeling environment, a SME would be required to identify a subset of lower level metrics that drive the provided performance objectives, which are usually high level metrics. This could prove to be difficult for a SME, especially when more than one objective is provided and they are conflicting.

Identifying a set of low level metrics that drive the performance objectives is important because it can eventually guide which technologies are pursued. In order for decision makers to decide which metrics to focus on, they may require not only an enumeration of potentially important metrics, but a quantification of the relative importance of the metrics in the subset to each other. Obtaining a quantitative measure of the relative importance could be an extremely difficult task for SMEs and it would likely require the opinion of multiple SMEs with varying levels of expertise in the many required disciplines. A modeling environment that captures multiple levels of system performance metrics could provide relief for the SMEs when it comes to this task.

Furthermore, the use of an analysis model will open the door to various quantitative assessments, such as sensitivity analysis. It was observed previously that a SA can be used to identify the lower level metrics driving the system level metrics. SA's also have the ability to provide desired quantitative measures of relative importance. Therefore, based on these observations, the following hypothesis was formed:

Hypothesis 1.2: *A model-driven environment that captures both the provided system-level performance objectives as well as the lower level system components will enable the identification of important metrics that drive the performance objective and their relative importance can be calculated and a rank order can be determined.*

Identification of important low-level metrics driving the performance objectives is important, but it is also beneficial to understand how much of a capability improvement is required. Enumeration of a set of important low-level metrics can help identify the types of solutions, or paths, that should be followed to achieve the provided objectives. Technologies generally do not map directly to system level metrics and are instead described by the capabilities they provide at the sub-system or component level. Therefore, the system level performance objectives may need to be decomposed into lower-level objectives, or impacts. The impacts can be enumerated as performance deltas from a baseline set of metrics. Generally, there will be more than one way a system level objective can be met and each set of required impacts forms a scenario that a development program could choose to pursue. Building from this observation, the following term will be utilized:

Impact Scenario: Set of impacts, provided in the form of deltas from a baseline value of a low-level metric, that are required for a high level metric to be met

The enumeration of potential impact scenarios is important because decision makers desire to have many possible avenues to choose from. This task could prove to be difficult for SMEs because they may not know practical improvements, or deltas, to assume for disciplines of the system outside their area of expertise or may not know the compatibility of different combinations. Therefore, a quantitative method that enables the identification of impact scenarios through the use of a modeling environment is desired.

Further investigation into the field of technology analysis led to the topic of technology forecasting. Forecasting means providing, or predicting, a view of the future. Engineers desire to forecast the impact a technology can have on a system's performance before it can be measured or the technology is fully matured[57]. Therefore, the objective of technology forecasting is to use a systematic approach to provide information that can be used to support technology or system related decision making.[109]

There are two different types of forecasts: exploratory and normative. A normative forecast can be perceived as a top-down assessment. These forecasts start with a provided objective, such as a performance objective, that has an unknown feasibility. The goal of the forecast is to work backwards from the provided objective to determine whether it is currently feasible and/or what types of improvement are required to make it feasible.[109, 57]

A specific normative forecasting technique common in the literature is Technology Impact Forecasting (TIF). TIF utilizes an existing modeling environment to provide a quantitative assessment of the capabilities that are required to meet a provided system performance objective. The TIF process begins with identification of all potential impact variables, and their appropriate ranges. Meta-models, or surrogate models, are then fit to the relevant outputs of the analysis code as a function of the identified impact variables.[57] The meta-models enable a designer to investigate if performance objectives can be met with specific variable settings.[55] The impact variable settings that enable the performance objectives to be met are indicative of the types of technology impacts that decision makers should look for in potential technologies.

Provided this information, it is observed that the TIF methodology can operate on a system model to provide the capabilities required of varying system components to meet an overarching system level objective. Since the nature of the TIF assessment is to determine forecasted performance values, then the models utilized are desired to be physics based models because the new systems can potentially fall outside of an existing database used for empirical models. Based on these observations, the following hypothesis was formulated:

Hypothesis 1.3: *A large set of potential "impact scenarios" that enable performance objectives to be met can be identified through technology impact forecasting and a physics based modeling and simulation environment that captures the provided objectives and lower level system components.*

3.2 Technology Selection Formulation

The second phase of development is *Technology Selection*. This phase addresses a single key question, which is:

- What technologies should be pursued?

The focus of this phase is to provide information that will facilitate the down-selection of the technologies that will be further developed. In some situations a super-set of technologies may exist for the program to down-select from, but in other cases the super-set may need to be formulated. After a set of technologies is determined, relevant technology portfolios must be generated and evaluated to aid technology down-selection.

3.2.1 Technology Portfolio Formulation

Technologies can be chosen for development based upon their individual merit or due to the integrated merit of a group of technologies. When aggressive performance goals are set for new systems, a set of technologies will be required because no single technology will be able to provide the new capabilities. Technologies must work together with other elements of a system to meet system level performance objectives. Therefore, a development program may want to invest in a suite, or portfolio, of technologies that, altogether, can provide the best chance of meeting the provided objectives. Building from these observations, the following term is defined:

Technology Portfolio: Set of technologies that, when integrated into a system together, provide the potential for a performance goal, or set of performance goals, to be met.

Identification of potentially viable technology portfolios from a technology super-set must be completed before technology down-selection can begin. It is possible there exists multiple technology combinations that can achieve the objectives of a single impact scenario, and when multiple impact scenarios exist there can be a large number of potential technology portfolios. Therefore, the first research question defined for Phase 2 is:

Research Question 2.1: How can viable technology portfolios be identified?

A technology portfolio is selected based upon its defining characteristics. These characteristics can be related to how it performs, its current readiness, how much it is expected to cost, and many other aspects that may not be possible to objectively quantify. The desired characteristics of the technology portfolio that is ultimately pursued also guides how technology portfolio alternatives are formulated. For example, if portfolios with a large performance potential are desired and the technology uncertainty is considered secondary, then it would be beneficial to identify high performing technologies and utilize them to formulate potential portfolios. Furthermore, when the selection criteria for the technology portfolio is unknown, technology portfolios with varying characteristics should be formulated and analyzed.

If the number of technologies under consideration is small, then it may be possible to formulate and analyze all potential technology portfolios. However, as the number of technologies increases the number of potential technology portfolios will expand past the point of a full-factorial portfolio generation due to computational resources. Therefore, the technologies will have to be prioritized for technology portfolio formulation. Furthermore, the ultimate number of technologies included for a single portfolio would have to be defined before the portfolios could be formulated. This number will most likely be limited by either the amount of resources available or other programmatic factors.

This research focuses on evaluating technologies and technology portfolios based upon their performance risk and readiness risk. Therefore, aspects of performance and readiness of the individual technologies is explored for prioritization and portfolio formulation. With regards to performance, the identification of technology portfolios requires information on the expected impacts of technologies and compatibility of technologies within the super-set. The expected impacts of a single technology, including both beneficial impacts and detrimental impacts, are the result of forecasting. Unlike the TIF forecasting process, this type of forecasting is exploratory in nature. An exploratory forecast is based upon extending past trends into the future along an expected progression path[109, 57]. Exploratory forecasts can also be seen as bottom-up forecasts, where you begin with your current state and assess where you could be in the future. Exploratory forecasts rely on the assumption that the expected path of progression, which is based on historical trends, is correct. A common assumption based on the examination of a large number of past technologies is that a technology's performance follows a logistic,'S', shaped curve [109]. An example of this common S-curve is shown in Figure 25.

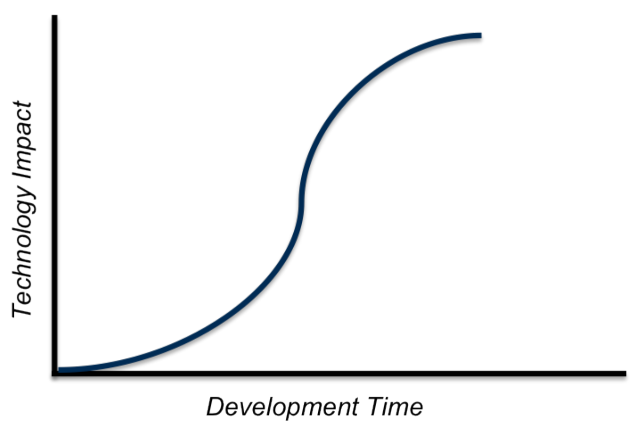

Figure 25: Technology Impact S-Curve Trend

Quantitative exploratory forecasting requires quantitative representation of technologies; however, Twiss acknowledges that representation of technologies in a quantitative manner is not easy, especially if the physics is not completely understood[109]. This is overcome by representing technologies, or potential impacts of technologies, as defined deltas with respect to a current system baseline[70, 55]. These delta's are referred to as "k-factors" and they directly modify computed metrics during the analysis process, which in turn simulate technology benefits and penalties. The technology k-factors provide a way to simulate the discontinuity of technology benefits or penalties in a generic way [70, 57, 55]. Examples of computed metrics that k-factors alter are specific fuel consumption or cruise drag, both of which can be outputs of one assessment tool and inputs to another. Equation 23 demonstrates how k-factors could be used in the calculation of fuel weight.

$$W_{fuel} = \left[(k_{W_{empty}} * W_{empty}) + W_{payload}\right] \left[exp\left(\frac{Range * k_{TSFC} * TSFC}{V} * \frac{k_{C_D}}{k_{C_L}} * \frac{D}{L}\right) - 1\right] \tag{23}$$

As previously noted, it may be easier to map technologies to lower level metrics that are closer to the sub-system or component level of the system where the technologies themselves will be integrated. Therefore, technologies may be mapped directly to the identified impact scenarios since they are sets of objectives at a lower level of the system. The impact variables within a given impact scenario can be augmented with technology k-factors if an identified technology has a relevant impact. It is also possible to have technologies within the super-set that map to several different levels of the system model. For example, it is possible a system model is the integration of three separate analysis tools in a hierarchical manner where the outputs of one map directly to the inputs of the next. The impacts of some technologies may map directly to input variables of the first analysis tool, which would be the lowest represented level of the system, and the impacts of others may map to the outputs of the second analysis tool. This situation is depicted in Figure 26 through a two module vehicle sizing tool. In this example outputs of an aerodynamics analysis tool go into a propulsion analysis tool, and vice versa. It is shown that two k-factors, k_1 and k_2, map to the lift to drag ratio and parasite drag and two other k-factors, k_3 and k_4, map to the fan pressure ratio (FPR) and the burner efficiency.

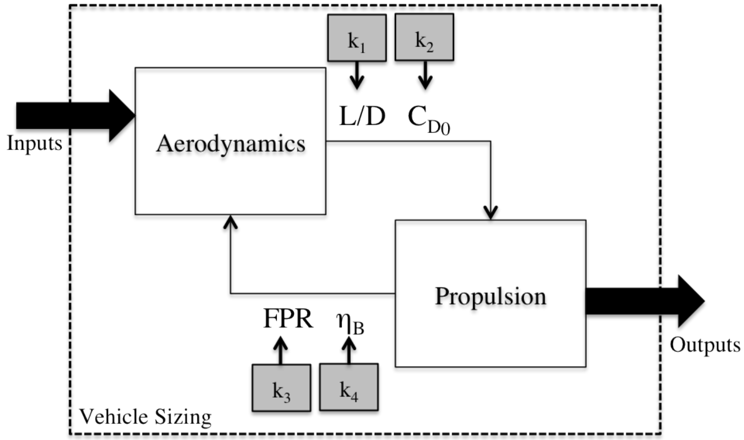

Figure 26: Example of k-factor mapping to a vehicle sizing environment.

The TIES methodology utilizes the k-factor approach to model technologies and facilitate technology portfolio down-selection. Within TIES, specific technologies are identified for infusion and their k-factor vector is formulated. The TIES methodology does not provide a method for prioritizing technologies for portfolio formulation, but its use of the technology impact matrix (TIM) and technology compatibility matrix (TCM) can be leveraged. If the exact k-factor value, or vector of values, for a given technology is not known due to its immaturity a probability distribution can be utilized. The addition of uncertainty quantification techniques to the exploratory forecasting process can enable the assessment of the expected impact a single technology will have.

The results of the sensitivity analyses conducted in *Strategic Planning* provide a ranked list of low-level impacts with respect to the performance objectives. When the impacts of all technologies are mapped to the technology k-factors in the TIM, technologies that map to key impacts can be readily identified. This would enable technology prioritization based upon the importance of each technology's expected impacts. Technology compatibility information provided in the TCM and other non-performance information could then be utilized to formulate viable technology portfolios composed of the prioritized technologies.

Based on theses observations regarding exploratory forecasting techniques and the TIES methodology, the following hypothesis was formed:

Hypothesis 2.1: *The mapping of technology impacts to important low level metrics of a modeling and simulation environment that captures the performance objectives will enable sets of potentially viable technology scenarios to be identified.*

3.2.2 Portfolio Risk Assessment

Once individual technologies and technology scenarios have been identified, they must be assessed to provide the information that enables trade-offs to be made. Therefore, the proper value metrics and the processes for calculating the metrics must be identified. This leads to the following research questions:

Research Question 2.2: How should readiness risk of technology scenarios be communicated?

Research Question 2.3: How should performance risk of technology scenarios be communicated?

It was previously discussed that a technology portfolio may be selected based on a variety of characteristics, and the objective of this research is to address characteristics of performance and readiness. Identification of the information that properly communicates both performance risk and readiness risk to decision makers was done by first identifying the relevant decision scenarios. In this context the term *decision scenario* refers to the internal preferences of the decision maker with regard to topics such as overall readiness, expected performance, and the potential consequences of both. By utilizing past experiences with technology development programs and lessons learned through background research, a thought experiment was performed and the following decision scenarios were identified:

1. A technology portfolio that has the potential to provide an incremental performance improvement but low readiness risk is desired.

2. A technology portfolio that has the potential to provide large improvements in performance is desired, and readiness risk is not considered.

3. A technology portfolio that has low to moderate readiness and performance risk is desired.

4. A technology portfolio that has low performance risk is desired.

Based upon these decision scenarios, clear measures of performance risk and readiness risk are required. Recall that the definition of risk provided in Chapter One requires a measure of likelihood and a measure of consequence for each type of risk under consideration. Therefore, the objective is to identify measures of performance likelihood and consequence and measures of readiness likelihood and consequence that enable the trade-offs described by the decision scenarios defined above. Furthermore, since this phase of the development process deals with comparing technology portfolios and not necessarily individual technologies, the likelihood and consequence metrics will need to be representative of a set of technologies. Therefore, it may be required to formulate aggregates of some metrics.

3.2.2.1 Readiness Risk

For readiness risk, measures of likelihood need to communicate how likely it is a portfolio of technologies will achieve the desired readiness level. The likelihood that a single technology achieves a desired level of readiness is a function of the technology's current readiness level and the anticipated difficulty of filling in the readiness gap.

This also applies to an entire technology portfolio, where the likelihood is a function of the portfolio's current readiness and the expected difficulty of increasing it.

As for the consequence aspect of readiness risk, a measure that communicates the negative impact on the system due to immature technologies is required. It was acknowledged in Chapter One that technologies that fail to reach a high level of readiness before system development begins cause schedule and cost overruns to the program because system developers are then potentially responsible with finishing the technology development process. Therefore, the current readiness, or the gap in readiness, could be utilized as a measure of consequence. In this context, a high readiness level corresponds to a low consequence.

In conclusion, it is believed that readiness risk can be quantified through measures of difficulty and measures of readiness. Therefore, aggregate measures that communicate both of these for a set of technologies is required. It has been established through the background research that the most common metric used to communicate readiness is TRL. Therefore, for this thesis the overall readiness of a technology will be communicated using the TRL metric. However, there is an additional need to define a metric that is representative of the varying readiness levels of technologies within a set. It was noted in Chapter Two that mathematically combining values from an ordinal scale, such as TRL, is not an accepted practice so a new measure or method is required to overcome this.

Conrow acknowledged the limits placed on the TRL metric from its ordinal scale, such as the inability to calculate the mean TRL of a set of technologies. An ordinal scale has different levels that are monotonic and provide a rank order; however, they do not allow anything to be said about the relative separation between the different levels. For example, a technology with a TRL of 8 does is not necessarily twice as mature as a technology that with a TRL of 4.

To overcome this limiting factor of the TRL metric, Conrow proposed an approach to turn the ordinal TRL scale into a cardinal scale. His process utilized the Analytic Hierarchy Process(AHP) to estimate cardinal TRL coefficients, which he then transformed into the cardinal scale. Table 5 displays the cardinal TRL values that resulted from his work.[22] The resulting cardinal TRL values aim to represent the true readiness level of a technology with respect to a fully developed, TRL 9 technology. Therefore, they aim to take into consideration the varying amount of readiness increase from one TRL to the next. Recalling the previous example, the cardinal TRL values for TRL 4 and TRL 8 are 1.14 and 6.81, respectively. Therefore, you can now say that the TRL 8 technology is more than five times more mature than the TRL 4 technology.

Table 5: Cardinal TRL definitions [22]

Ordinal TRL Values	Cardinal TRL Values
1	0.26
2	0.53
3	0.71
4	1.14
5	1.97
6	2.74
7	4.26
8	6.81
9	9.00

The creation of the cardinal TRL scale enables the calculation of readiness statistics for a technology portfolio if the TRL of each individual technology is known. These statistics can then be used as measures of the overall readiness of the entire technology portfolio. Therefore, a measure that can potentially communicate the performance consequence for a technology portfolio can be calculated.

It was observed in Chapter Two that there are three different types of development difficulty. The first type of difficulty is related to the relative difficulty between readiness levels. The second type of difficulty is the relative difficulty among different technologies. The final type of difficulty is the difficulty of achieving a set performance goal. Of these three types, only the first and second are relevant to readiness risk. Furthermore, the first type of difficulty is inherently captured through the use of the cardinal TRL scale. Therefore, the only type of difficulty that remains is relative difficulty in achieving a readiness level among different technologies.

Two measures of difficulty were presented in Chapter Two, AD^2 and $R\&D^3$. It was observed that $R\&D^3$ is setup to capture the difficulty in achieving a performance goal, so it is not directly useful for the quantification of readiness risk. Furthermore, it was observed that while AD^2 does attempt to capture the relative difficulty among technologies, there is no clear process on how it should be calculated. Therefore, aspects of the definition AD^2 could be utilized for readiness risk, but the metric itself may not be viable.

3.2.2.2 Performance Risk

For performance risk, the measures of likelihood and consequence will be the result of quantitative, probabilistic analysis. Risk assessments have migrated from qualitative assessments to sophisticated quantitative risk assessments. NASA originally used probabilistic risk assessment (PRA) methods in the 1960s following the loss of Apollo 1 [51]. However, conservative estimates led to disapprovingly high failure probabilities for future Apollo missions [51, 105] and NASA reverted back to qualitative methods like Hazard Analysis and FMEA [105]. This continued to be the status-quo within NASA until the Slay committee recommended reverting back to PRA approaches for Shuttle assessments in 1986 after the Challenger accident [105]. Between the 1960s and 1986 PRA methods had matured within the nuclear industry.

The formalization of quantitative, probabilistic risk assessment (PRA) is the product of the nuclear industry [51]. As the number of nuclear power plants increased in the 1970s, the nuclear industry was pressured to focus on their risk assessments to ease public safety concerns. A study was conducted in 1972 that is known as the Reactor Safety Study (RSS), or the Rasmussen Report and WASH-1400 [51]. The study first used fault trees, but eventually transitioned into event tree analysis to remedy the constraints in time and resources. Probabilities for the different events within the event trees were estimated and a probabilistic assessment was carried out for each disaster scenario defined. The notion of scenarios, which is the first part of the risk triplet, was introduced by WASH-1400.

WASH-1400 showed that some of the more likely, less severe initiating events could lead to more severe accidents than initially anticipated. Overall, though, the results showed that the likelihood of nuclear power disasters were very low. While these results should have been seen as a good way to ease the safety concern, WASH-1400 faced many critics when it was finally published and PRA was not immediately accepted.[105] The data used to estimate the probabilistic information was very limited and some disagreed that the creation of accident scenarios was a logical approach. However, after further review the main concepts of WASH-1400, such as the use of fault trees and event trees together and the identification of accident pathways, were praised and accepted in the nuclear community and beyond.

In the current state, the most important components of PRA is the clear identification of the scenario being examined and a calculation of the uncertainty surrounding it. The goal of PRA is to quantify the uncertainty surrounding the risk scenario and translate it into a risk measure, whether it be a performance risk measure, safety risk measure, schedule risk measure, etc. The risk measure can then be utilized to compare all identified risks or risk scenarios of a program throughout the program's life-cycle.

If each possible scenario is modeled and the probability of occurrence of each is accounted for, it will result in a probability distribution of forecasted outcomes [105]. The probability distribution enumerates all possible outcomes, but does not provide a precise risk metric or measure. In this context, the term risk metric refers to probabilistic measures that might appear in a decision model[105]. Examples of such things include the probability of consequences or the expected consequences. For performance risk the probability of consequences would be the probability of not meeting a defined performance objective, which can be determined from a CDF, and the expected consequences could be how far the forecasted system is from meeting the performance objective.

Risk metrics, or other methods of communicating outputs of PRA, are needed to compare different alternatives or scenarios to aid in decision making. Additionally, some decisions may depend on multiple risk measures, such as a cost risk measure and a schedule risk measure. The previously discussed risk measure, the probability of success of meeting a given objective, is just one example of a risk measure. Another identified potential risk measure is the mean values of the PRA output PDFs [105]. Chapter Two provided an enumeration of not only quantitative, probabilistic techniques, but also measures of uncertainty that can be utilized to aid identification of potential measures that will aid the communication of performance risk. For performance likelihood a measure that communicates how likely it is for the portfolio to achieve the set goals is desired. Therefore, measures that communicate either the expected performance, the spread of the potential performance, or both are considered. These include the mean, variance, and probability of success (POS).

For performance consequence, a measure that quantifies how bad the technology portfolio could potentially perform is required. Two specific metrics are appropriate for this measure: the tail conditional expectation (TCE) and the worst possible value.

The TCE was presented in Chapter Two and is the mean value of the portion of the probability distribution that is outside the goal value. It provides a way to characterize the tail of a distribution in a single measure. The worst possible value is exactly as it sounds; it is the worst objective value observed during the probabilistic analysis of a given technology portfolio.

3.2.2.3 Risk Communication

Presentation of the risk measures of different alternatives or different scenarios is important. The level of detail and the style of presentation used to communicate risk results depend on the risk assessment objectives. Graphical and tabular displays are effective means for communicating risk assessment results[105]. NASA's PRA handbook suggests that the following information can be successfully communicated using graphical or tabular form: likelihood values, lists of dominant risk scenarios, relative ranking of scenarios or alternatives based on likelihood or risk metric values, and consequence estimates [105].

One common form for representing PRA results is through a risk matrix. A risk matrix provides a way to show two-dimensional results without reducing them to one dimension. One axis of the matrix can represent the likelihood of occurrence of a scenario and the other axis can represent a measure of the consequence of the scenario should it occur. utilization of a risk matrix goes hand in hand with the utilization of the risk triplet definition. Recall, the risk triplet definition is attractive because it does not attempt to shrink risk results into a one dimensional metric that could confuse highly likely, low consequence scenarios with less likely, high consequence scenarios.

An example of a risk matrix is displayed in Figure 27. In this depiction, numbers one through five represent different scenarios being assessed. The red/yellow/green squares attempt to characterize areas of high/mid/low risk; the function, or separation scheme, used to determine the risk boundaries is up to the the entity, or person, that will be utilizing the risk matrix results. Another way of distinguishing among the severity of risks displayed on the risk matrix is to discretize the space and assign each block a different number. Large numbers indicate high risk areas.

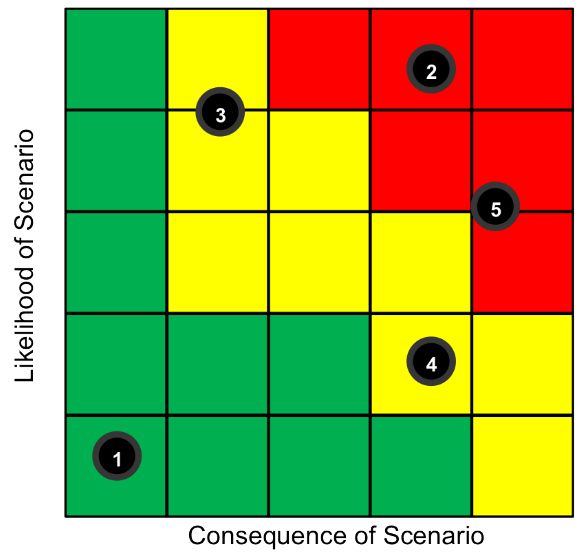

Figure 27: Notional Risk Matrix

The observations and discussion about potential readiness and performance risk measures, risk assessment techniques, and risk communication methods leads to the following hypotheses:

Hypothesis 2.2: *A risk depiction that provides a measure representative of the readiness of the entire portfolio and the expected difficulty of increasing the readiness for each portfolio will yield readiness risk information that enables the identified decision scenarios to be made.*

Hypothesis 2.3: *A risk depiction that provides a measure of how far away from the objectives a scenario could end up and a measure of the probability of successfully* *meeting the objectives will yield performance risk information that enables the identified decision scenarios to be made.*

3.2.3 Supplemental Technology Identification

It is recognized that after a technology portfolio is selected, there may be remaining resources or added resources that enable the selection of additional technologies. Therefore, the final part of the *Technology Selection* formulation involves the selection of technologies based upon their individual merit. Information regarding how the individual technologies affect readiness and performance of a predetermined scenario is then required. This leads to the following research question:

Research Question 2.4: What information enables comparison of individual technologies for the purpose of combining them with a selected technology scenario?

As previously demonstrated, the next step of the research process is to identify relevant decision scenarios. There are three identified scenario for why technologies would be selected and they are as follows:

- Select a technology that can serve as a backup for a technology that has a high difficulty value
- Select a technology that can serve as a backup for a technology that drives the POS

For readiness risk, the previous hypothesis involved aggregates of both readiness and difficulty. The calculation of aggregates requires the individual values for each technology be readily available. Therefore, if a technology is being selected to provide redundancy for a high difficulty technology, no additional information would be required for decision makers. In contrast, when a technology is being selected to increase POS, new information will be required to aid decision makers. In general, the POS of each scenario will be the result of uncertainty propagation and have been previously been calculated and the impact distributions for each technology will be available. However, no information regarding how an individual technology within the scenario is affecting the portfolio's POS of meeting a performance objective. Probability distributions of one technology, or a subset of technologies, could be causing the response distribution to change in a way that negatively affects the ability to meet an objective. Therefore, information on how each technology affects the POS could provide insight to decision makers. Based on this observation, the following hypothesis was formulated:

Hypothesis 2.4: *If the sensitivity of the objectives' POS to the technologies in a technology portfolio is quantified it will provide preference for remaining technologies under consideration.*

3.3 Technology Experimentation Formulation

3.3.1 Readiness Assessment Procedure

The proceeding phases will utilize a measure of readiness, so an appropriate measure must be identified. It was observed in the background research that the current standard for measuring and communicating readiness is the TRL scale. It was also demonstrated that shortcomings of the TRL scale have been identified by various entities. The ability to accurately measure and communicate readiness is essential in technology development and a fundamental part of this research. Therefore, the following research question will be addressed:

Research Question 3.0: What is the appropriate way to measure and communicate the readiness of technologies?

Through a qualitative assessment of the identified shortcomings, it was concluded in Chapter Two that the use ambiguous terms to define the different levels of the TRL scale should be addressed if TRL is to be utilized. The first step in addressing the ambiguous terms is identifying them. A closer look at the TRL definitions provided in Figure 13 and Figure 14 resulted in the identification of different readiness attributes. When defined and synthesized, these attributes of readiness create the overall TRL measure. The attributes include aspects of the test environment, the entity being tested, and the overall purpose of the TRL level.

This observation is one that was also made by Jimenez and Mavris in their work on the inclusion of integration in readiness assessments.[46] In their work, they utilized the terms *fit*, *form*, and *function* to identify readiness attributes and integration attributes relevant to technology development. Fit, form, and function are terms formalized by the the military as item descriptors for military configuration management standard. Fit is defined as "the ability of an item to physically interface or interconnect with or become an integral part of another". Form is defined as "the shape, size, dimensions, mass, weight, and other visual parameters that uniquely characterize an item". Function is defined as "the action or actions which an item is designed to perform".[1]

These three basic concepts can be utilized to help further identify relevant attributes of readiness. Jimenez and Mavris utilized these terms in conjunction with the TRL definitions to identify integration-specific readiness attributes. Figure 17 depicted the results of their attribute analysis for TRL 3 to TRL 7. The very low TRL levels, 1 and 2, are not represented because they found no aspects of integration are attempted at these levels. The highest TRL levels, 8 and 9, are not represented because integration should be fully realized at this phase of development. The figure also displays two different aspects of technology development, the physical experimentation and the analytical representation of the technology. The left column depicts the integration status of the physical experimentation relevant to each of the provided TRL levels. It depicts aspects of both the test environment and the test articles. The right column depicts the aspects of integration that are being modeled, or able to be modeled, at each of the provided TRL levels.

Jimenez and Mavris' use of the TRL definitions and the fit, form, and function terms provide an adequate starting point for the identification of all relevant readiness attributes. Furthermore, it provides a way to overcome one of the identified shortcomings of the TRL metric, which was the lack of inclusion of integration. It is believed that further decomposition of the TRL level definitions into a complete set of attributes will make the TRL metric less ambiguous and more transparent. However, a method for proper communication of what is entailed by each TRL level is still desired. In an attempt to fill this void, the area of morphological analysis was explored.

Morphological analysis is a method that traces back to the 13th century and was formalized in 1942 by Swiss astronomer Zwicky. The basic idea behind morphological analysis is to break down the subject under investigation into a number of fundamental dimensions that completely describe the subject. Wissema concludes that an early example of of morphological analysis can be found in Mendeleyev's periodic table of elements because the arranged the elements in the table according to the many different properties that define them.[117]

The process of morphological analysis consists of five main steps. The first step is to identify the different dimensions, or functions, of the subject under investigation. The second step is to identify the different ways each dimension can manifest itself. Next, all of the potential combinations represented by the different dimensions choices are calculated. The final two steps involve identifying the practical combinations and then reducing this set even further to choose a final combination.

Morphological analysis has been used in many disciplines, including aircraft design and technology development. Several researchers have utilized morphological analysis for technology forecasting[110, 117, 119, 59]. Wissema concluded with his research that morhpological analysis provides a good systematic starting point for a technology forecasting framework or investigation, but ultimately should be supplemented with other methods. He also notes that morphological analysis may be confusing at the beginning of problem formulation, but will be come clearer as more is understood about the subject. Kirby utilized morphological analysis as part of her TIES methodology that was previously discussed. She utilized the process to decompose the aircraft system into different sub-systems and components and then identify different potential vehicle architectures. This concept worked very well to enumerate the different aircraft integration concepts and book keep the system assumptions during technology development. Figure 28 displays a simple morphological matrix for aircraft architecture definition.

Choice / Attribute	1	2	3	4
Configuration	Tube and Wing	HWB	Over the rotor	Double bubble
Engine Type	Direct drive	Geared fan		
Materials	All metal	Partial composites		

Figure 28: Example morphological matrix created for aircraft architecture selection

It is believed that a morphological analysis can be utilized to represent the different readiness attributes. The resulting morphological matrix could then be used to characterize each level of the TRL scale. A first attempt at organizing the recognized attributes of readiness is displayed in

These observations therefore lead to the following hypothesis:

Hypothesis 3.0: *If morphological analysis is used to enumerate all relevant readiness attributes and the corresponding system specific choices, a measurement of readiness that is traceable and complete will be created.*

Sub-attribute	Sub-attribute choices			
Type of test environment	Computer Simulated	Lab	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	Simplified, some assumptions	Controlled	Operational
Fidelity of model tested	Non-physical	Prototype, non-working parts	Prototype, working parts	Actual hardware
Scale of model tested	Sub-scale	Full-scale		
Level of test	Single technology	Single sub-system, multiple technologies	Multiple sub-systems	Full system

Figure 29: Initial morphological analysis formulation for assessing technology readiness.

3.3.2 Experiment Design Procedure

The third phase of development is *Technology Experimentation.* This phase addresses a single key question, which is:

- What development activities should be performed?

Development activities are planned to gain new information about the technologies in question. As new information is gained, it is expected that the readiness will increase and the uncertainty surrounding the performance will be reduced. The linkage between technology readiness and performance uncertainty has been acknowledged in the literature. Furthermore, several experiment planning experiment planning techniques that integrate quantitative uncertainty analysis into their processes have been identified.

3.3.2.1 Existing Experiment Design Processes

It has been acknowledged that performance uncertainty reduction can be used as a surrogate for an increase in technology or system readiness. Jimenez et al.[45] states that aspects of readiness can be represented by probability distributions. In their research they link deterministic TRL values to the shape of probability distribution around the technology performance metrics. As shown in Figure 30, the range the function covers shrinks and the kurtosis increases as the TRL increases, which represents less variability and more knowledge of the true value of the technology impact factor. The authors used a Weibull distribution as the probability model and ultimately determined appropriate settings for the distribution parameters based on TRL. It is stated that this method is only applicable through TRL 7 because enough knowledge should be gained by TRL 8 and 9 to support deterministic impact values.

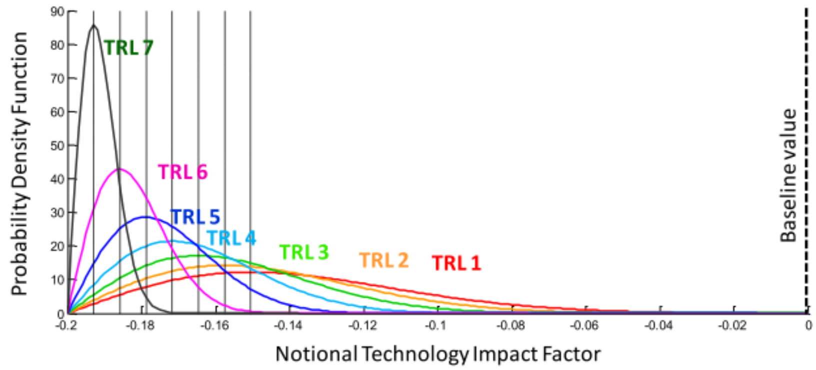

Figure 30: Probabilistic Technology Impact with Varying TRL.[Reproduced from [45]]

The concept of linking the level of a technology's readiness to probability distributions for performance metrics presented by Jimenez et al. is one that is echoed in the literature by various authors. In general, it is acknowledged that decreasing uncertainty surrounding expected performance corresponds to increasing readiness. Furthermore, it has also been acknowledged that experimentation planned during development can be planned to directly attack uncertainty sources, which will in turn advance the readiness level upon completion.

Largent[61] developed the Technology Development Planning and Management (TDPM) process to provide a structured process that aims to increase technology readiness by facilitating a decrease in performance uncertainty and programmatic risk. The TDPM process encompasses defining technologies, estimating their technical uncertainties, enumerating potential experiments to tackle the uncertainties, and a risk assessment of the potential experiments to facilitate down-selection.

Largent utilizes the TRL scale for assessing the starting and ending readiness levels of all technologies under development. Largent suggests an analysis-based assessment that utilizes a modeling and simulation environment, Monte Carlo Simulation (MCS), and Response Surface Methodology (RSM). This assessment is conducted to determine which uncertainties are most important and should therefore be reduced first.

The results of the probabilistic analysis are displayed on a Pareto Chart to rank the uncertainty metric ranges in order of importance.

In TDPM it is suggested that experiments required to reduce uncertainty are developed by project managers and technology experts. Additionally, it is pointed out that previous development efforts for similar technologies and the TRL scale be used for identifying general activities to perform, but it is cautioned that if test articles are scaled the designer should first make sure the phenomena they wish to capture is scalable. Largent suggests the use of a project network analysis method by Michaels to form a project plan of experiments to help determine what experiments can be done in parallel and which must be done in series. After a project plan with acceptable risks is formulated, it is carried out and data is collected. The TDPM process can be viewed as an iterative process. Each time new data is available, the uncertainty distributions and cost and schedule predictions are updated. This enables an iterative experiment planning process.

Bjorkman [17] developed a methodology comprised of three frameworks and one process: Technical Uncertainty Sub-Framework, Uncertainty Priorities Sub-Framework, Uncertainty Reduction Objectives Sub-Framework, and Develop Test Options and Optimize Test Portfolio Process. She was motivated by testing and evaluation (TE) issues within the Department of Defense, where she says the attitude within the DoD is “TE is an expensive hurdle that stands in the way of acquiring the system of interest.” TE research identified literature focused on reducing the cost and identifying problems early in the process; however, the point of TE is not to reduce cost so cost is not an appropriate metric of value. Bjorkman states measuring the reduction in uncertainty the test provides is a better measure of value for stakeholders and decision makers. A way to translate the value of a test and risk attitudes toward a test into an overall metric is needed to determine an optimum test plan.

Bjorkman utilizes Shannons Information Entropy (SIE) for an uncertainty reduction value metric for the methodology; however, in the conclusions Bjorkman mentions SIE may be too conservative of a measure in some cases and suggests further investigation of the use of variance. Several techniques for uncertainty depiction are suggested, but ultimately Bjorkman does not recommend one specific technique and states uncertainty depiction is contingent on the problem at hand and its characteristics. The same conclusion is made for the selection of an uncertainty reduction technique.

The goal of the Uncertainty Priorities Sub-Framework is to determine how much effort should be applied to estimating the initial uncertainties and the desired uncertainty reduction for a single test. For uncertainty prioritization, Bjorkman uses the Pate-Cornell framework as a starting point and alters it to be more relevant to DOD TE. Like Pate-Cornells framework, there are six levels of uncertainty priority ranging from 0-5 with 5 being the highest priority. The levels are presented with descriptions and example applications. The descriptions of the levels use uncertainty as the descriptor metric (e.g. Identify all known uncertainty sources and types) while the example applications are described using risk and cost (e.g. Low risk upgrade with limited TE resources). This implies that a risk assessment is being conducted before the uncertainty priority assessment; it is unclear the relationship the author assumes among uncertainty, risk, and cost.

Bjorkman implores a Model-Based Systems Engineering (MBSE) approach for setting uncertainty reduction objectives that includes setting requirements, utilizing analytical models to allocate initial uncertainty budgets for technical performance metrics, and receiving input from test and design engineers to establish uncertainty reduction goals for each event. Technical performance metrics (TPMs) are defined by Roedly and Jones as the set of measurement activities used to provide the supplier and/or acquirer insight into progress in the definition and development of the technical solution, ongoing assessment of the associated risks and issues, and the likelihood of meeting the critical objectives of the acquirer. Bjorkman states that TPMs should have a time element, be focused on technical risk impacts on meeting critical objectives, and have a probability associated with them.

Bjorkman introduces the notion that depiction of TMPs, and their associated probabilities, through time is not a continuous reduction in uncertainty. Bjorkman estimates initial TPM uncertainties using a Monte Carlo method on the uncertainties associated with the components of the TPM measurement models; however, it is stated that any uncertainty estimation technique could be used, which makes it unclear why the Monte Carlo method was ultimately chosen. In summary, uncertainty reduction is done by utilization of a MC simulation technique embedded in a MBSE process to plan uncertainty reduction activities and assess their potential impacts. Shortcomings of this approach are the lack of an explicit way to design the candidate test events for maximum uncertainty reduction and an analytical approach to estimating the initial uncertainties for input variables.

The process of test planning utilized by Bjorkman is derived from Clemen and Reilly[21] and is designed to determine an optimum portfolio of test points under a set of constraints. This is achieved by maximizing test value or utility. Cost and budget constraints are identified, as well as the test objectives for each test within a given portfolio. If multiple goals or objectives are specified for a given test Bjorkman suggests either selecting the uncertainty with the highest priority, selecting the uncertainty that is easiest to measure, or combining all uncertainties into one metric using priority weights. It is also mentioned that tests that must be conducted in a specific manner be removed from the optimization process.

Next, multiple test options are developed. Bjorkman states there are three types of test design: statistically-based tests, demonstrations, and tests designed by SMEs. Statistically-based tests are often rigorously designed and assessed; however, SME designed tests could also be assessed with equal rigor to determine how they compare to other test designs. Demonstrations are usually designed to prove if a system or component works, and are not necessarily relevant to uncertainty reduction. When this is the case they should be removed from the optimization process. After all tests have been designed, they are then modeled and uncertainty reduction for each is estimated. Bjorkman states the uncertainty reduction can be used directly as the value, or stakeholder preferences can be incorporated to create a utility metric and it can be used as the value for optimization. Test portfolio optimization is completed through a knapsack approach, which implies the assumption that all tests must be conducted and none are optional. Sensitivity analysis is also mentioned, but no details are offered on what should be assessed or how it should be done.

Sankararaman[93] was motivated by the inclusion of increasingly complex architectures and advanced technologies in engineering systems, for which he provides an approach for cost-effective prioritization of experiments in order to meet uncertainty reduction targets in system level metrics. The methodology is Bayesian network-based and assumes a modeling and simulation environment of the system is available. Sankararamans methodology is aimed at answering the question of which test to do by employing a GSA to identify the parameters in the model that affect the system level uncertainty the most. Tests are then selected based on their ability to increase knowledge of the identified parameters. Sankararaman assumes experiments on separate subsystems are statistically independent and a model is available to predict the quantity directly being measured by each experiment considered. The metric chosen to represent uncertainty reduction for this methodology is variance reduction, and the effect of a particular test on variance reduction is quantified using Bayesian updating.

3.3.2.2 *Experiment Planning Gaps*

The generation and selection of testing portfolios for technology development is historically a bit of an art. The process relies strongly on the experience and input of subject matter experts (SME). While this is a good starting foundation, there is a push for more formal, quantitative methods with respect to all aspects of design and development of a new technology or system. Adding formalization to the design and selection of experiments in the testing portfolio is needed because development entities cannot afford to test the wrong articles or phenomena because it will delay the maturation progression of the technology.

As previously demonstrated, there exists some methodologies that aim to add this quantitative rigor to the experiment design process. Largent provides a very transparent, well thought out process in TDPM that includes all of the steps inherent to a decision making process. However, there are some shortcomings of his process. While some aspects are supported heavily by mathematical formulation, such as the iteration process, others lack the rigor. The design of the experiments for the project plan is left solely to SME opinion. Just as it is stated that it would be difficult for experts to assess the effects of metric uncertainty on system responses, it is believed it would be equally as hard for an expert to design an experiment to achieve a specified uncertainty reduction goal. Another shortcoming is the lack of an explicit risk management technique. Throughout Largents methodology development risk is stressed as a very important aspect. Therefore, it was expected a quantitative risk management technique would be central to the assessment phase of the process.

The work done by Bjorkman is also very thorough and provides an improvement on the previous state-of-the-art. She encourages the use of modeling and simulation, specifically physics based models when available, to facilitate the propagation of lower level uncertainties to system level metrics. It is realistic and appropriate that she suggests the probability distributions used for the lower level uncertainties can be formed using either SME input or test data if it is available. Additionally, she acknowledges the importance each experiment design decision (i.e. instrument precision, selection of test points) has on the potential value of the experiment.

There are, however, some shortcomings of this methodology. The predicted uncertainty reduction provided by each experiment is determined via SME opinion only. Additionally, the significance of each uncertainty present in the system is determined through subjective rankings only. For both of these tasks there is no use or suggested use of quantitative methods, even though a physics-based environment with an uncertainty propagation framework is assumed available. Finally, as mentioned previously, Bjorkman suggests lower level uncertainty distributions can be formed from data if it is available, but does not provide a method to do so.

All in all, Bjorkmans methodology can be thought of as an exploratory process because she assumes there is an existing set of experiments, which have already been designed, and her framework is used to predict how much value they can provide. The framework does not provide the capability to assess how perturbations in experiment design variables will affect the experiment's value without completely re-evaluating the experiment as a whole. Bjorkmans framework also does not provide a definitive method; it offers a subset of techniques for each step from which the user can choose. While the reasoning for not conducting the down-selection is understood (the optimal technique for each type of problem is not the same), it is felt that a consistent methodology with a set of guidelines will be more effective. Additionally, it is felt that a consistent methodology is more likely to be utilized by decision makers within technology development programs.

Sankararamans methodology provides a mathematically rigorous, quantitative approach to experiment selection based on uncertainty reduction. Additionally, many new methods are developed within the supporting research that enables uncertainty quantification and propagation for multiple model types and various data availability scenarios (specifics of uncertainty quantification methods relevant to this research will be mentioned in the following chapter). The shortcoming of Sankararamans method, with respect to the research objective of this thesis, is the parametric design of the experiments. Similar to Bjorkman, Sankararaman takes an exploratory approach and assumes the tests have been previously designed and his purpose is to assess them and select them. It is the desire of this research to design and select experiments through a normative approach, where the design of the experiment will not static and it will be changed to achieve maximum uncertainty reduction.

Overall, a few questions arise for the implementation of quantitative uncertainty information for communicating readiness. For example, if variance is used to represent uncertainty for each technology, should it be used to compare the readiness of different technologies? Additionally, when technologies provide different types of impacts (i.e. an engine technology that increases burner efficiency versus an airframe technology that reduces drag) what variance should be quoted: the technology-level metric variance or the system-level metric variance? The background literature in readiness assessments and technology development does not provide a clear-cut answer to these questions. Therefore, the use of quantitative probabilistic information to represent readiness for a given problem or system will require further investigation to determine the most relevant process and adequate measures.

In summary, three main shortcomings were identified with respect to the discussed experiment planning methodologies. First is the assumption made in all of the discussed methodologies that SMEs are able to plan a set of experiments and accurately estimate the amount of uncertainty they will reduce. Sankararaman and Bjorkman utilize this assumption to aid in the prioritization of resources. Largent utilizes it to determine if an uncertainty reduction goal will be met by a selected set of experiments. Through experience and research, it is believed that this assumption would not hold true during implementation. Therefore, a new concept for prioritization of experimentation resources is required.

The second identified shortcoming is the lack of consensus on the metric that should be used to represent the amount of uncertainty. Largent and Sankararaman both utilized variance to quantify uncertainty and uncertainty reduction, while Bjorkman utilized information entropy. The metric used to represent uncertainty is important because it also guides the type of quantitative analysis that is done to aid experiment planning. This research utilizes probability theory; therefore, variance will be considered for a measure of uncertainty but information entropy will not be explored.

The final shortcoming to be addressed is the lack of synthesis with qualitative aspects of readiness. The three experimental planning methodologies presented were identified because they represent the current state of the art with respect to the utilization of uncertainty quantification techniques. However, they all assume the information provided by the quantitative analysis is sufficient to aid further experiment planning and prioritization done by SMEs. While the results of the quantitative analysis will provide key performance information that would otherwise be unknown, it is believed other information may be either useful or required.

3.3.2.3 Experiment Design Process

The experiment planning methodologies discussed provide a good demonstration of how quantitative information can be utilized, but their shortcomings must be overcome. Based upon this discussion, a way to prioritize technologies for experimentation and an improved method for experiment design is desired. Experimentation can either be planned all at once or in an iterative process. In instances where experimentation resources need to be intelligently allocated, there is a need to to identify which technologies should be prioritized for experimentation. Therefore, the following research questions will first be addressed:

Research Question 3.1: How should performance risk of individual technologies be assessed and communicated to aid experiment selection?

Research Question 3.2: How should readiness risk of individual technologies be communicated to aid experiment selection?

In order to identify the type of information required to select a technology and then an experiment, the potential trade-offs that decision makers may be interested in (with respect to readiness and performance) must be enumerated. A thought experiment was conducted and the following decision scenarios were identified:

1. The overall uncertainty in the system responses should be decreased, therefore technologies that impact the uncertainty the most should be selected for experimentation.
2. Technologies that affect the POS should be selected for experimentation.
3. Readiness risk should be reduced, so the overall TRL should be increased by targeting low TRL technologies first.
4. Readiness risk should be reduced, so technologies with high difficulty should be targeted first.

In this phase of development the characteristics of individual technologies are compared to each other, which is similar to the situation assessed in RQ 2.4. This implies that the metrics previously identified for likelihood and consequence of both performance risk and readiness risk are relevant. Therefore, the following hypotheses were formulated:

Hypothesis 3.1: *The synthesis of a measure that quantifies the amount of uncertainty related to a technology impact and a measure that captures the impact a technology has on the POS of the performance objective will yield performance risk information that enables the identified experiment design decision scenarios to be made.*

Hypothesis 3.2: *A risk depiction that provides a measure representative of the current technology readiness and a measure of the anticipated difficulty to increase the readiness will yield readiness risk information that enables the identified experiment design decision scenarios to be made.*

After the technologies have been compared and prioritized for experimentation, the experiments need to be planned. This leads to the next research question:

Research Question 3.3: What is required to determine experimentation for a given technology?

The overall objective in technology development is to increase the readiness and pinpoint the system performance it will enable. Therefore, no matter which decision scenario is followed for technology prioritization, the planning process should remain the same and experiments should be planned to systematically achieve both of these goals simultaneously. It is believed that this will require a method that integrates of the guidelines that define each TRL level and aspects of performance uncertainty.

Linking the reduction of performance uncertainty to the TRL scale has not been explicitly seen in the literature. An idea was inspired by AFRL's TRL exit criteria, which was presented in Chapter Three in Table 4. The exit criteria for TRL 3-TRL 8 includes "*Documented test performance demonstrating agreement with analytical predictions*". It would be unrealistic to assume that performance at TRL 3 could be perfectly predicted through analytical tools due to the lack of available information. However, as the technology matures the analytical tools should be able to predict the performance within a decreased tolerance. Therefore, the allowable performance uncertainty threshold should decrease as TRL increases.

Establishing that uncertainty should reduce as TRL increases should alter the way experiment planning is carried out. In general, an experiment can be defined by the test article, test environment, and the purpose of the test. The selection of these defining characteristics should be done so that the resulting data and knowledge gained from the experiment reduces the uncertainty. Therefore, any experiment planning process needs to take this into consideration and output the appropriate experiment characteristics.

First, the selection of the experiment purpose will be addressed. Information that could assist experiment planning is an enumeration of general, potential experiment objectives. There are common objectives found in the literature and Bjorkman provided an enumeration of several along with examples in her research. Utilizing this enumeration and feedback from current technologists in industry, a working experiment taxonomy has been formulated. Table 6 shows the experiment objectives currently identified and potential questions an experiment with that given objective could aim to answer with experimental data.

A general trend with respect to the order of the experiment objectives in the experiment taxonomy is observed. The objectives trend from gaining basic, general knowledge, to gaining increased detailed knowledge about the test article. For example, it is expected that an experiment to generally characterize a phenomena must be completed before an experiment that aims to calibrate a model of the phenomena is performed. This fits with the general progression of how a technology is developed as well; first its basic phenomena is identified and characterized, and then each subsequent examination increases the knowledge until detailed information is known and a

Table 6: Experiment Taxonomy

Experiment Objective	Questions
System Characterization	What type of phenomena are observed?
	What is the causality of an observed phenomenon?
	Does an observed phenomenon scale?
	What are the interactions among system components?
Model Construction	What are the governing physics of the observed phenomena?
	What are the appropriate types of models to use to represent the governing physics?
Model Calibration	What are the appropriate settings for the model parameters?
Model Validation	How well does the current model of the system predict experimental observations?
Uncertainty Reduction	What is the (more) exact value for a model parameter?
	What is the (more) exact performance for a given design?
Feasibility Study	Is this concept feasible?
	Will this concept work the way it is designed?
	Will multiple components work when integrated?

detailed model exists (or could exist). Therefore, it can be inferred that a taxonomy can provide a general progression of learning which can be used to identify what has previously been accomplished and what is remaining.

The experiment taxonomy provides guidelines of how to assess a phenomenon, but does not provide insight into how to select a phenomena for further experimentation. It is believed that this aspect of an experiment's purpose can be accomplished through quantitative uncertainty analysis. Probabilistic analysis provides information that can be utilized during experimentation planning for more than just technology prioritization. It was previously acknowledged that technologies may have more than one impact at the sub-system or component level. Depending on the nature of a technology, it may prove difficult to plan a single experiment that is able to capture all aspects of its performance. If a sensitivity analysis can be performed at the technology impact level for the selected technology, the impacts can be ranked based upon their uncertainty contribution. This information can then be used to select the type of information required to further quantify the prioritized technology impact. Furthermore, this will identify the type of measurements required to produce the desired information.

Once the purpose of the experiment is determined, the test article and test environment need to be selected. It was acknowledged through RQ 3.0 and its corresponding hypothesis that the definitions of the TRL levels inherently provide attributes that define the type of experimentation that is conducted throughout technology development. Figure 29 shows the initial morphological analysis formulation, which includes aspects of the test article and test environment. Each attribute has a progression of options, from the lowest fidelity option to the highest fidelity option. As a technology progresses through TRL levels, the characteristics that define the experiments performed will be mapped to options that are further to the right side. Furthermore, it is acknowledged that the definition of TRL levels though the morphological analysis can be seen as standards for required experimentation.

Meeting the experiment standards alone may not provide the defined uncertainty reduction goals. Therefore, more guidance is required. First, the different sources of uncertainty that contribute to the overall uncertainty surrounding the technology impact should be enumerated. It has been established that sources of uncertainty can be characterized as either epistemic uncertainty or aleatory uncertainty, and both types of uncertainty may exist when the exact performance is an unknown quantity. While it is important to include all sources in the quantification process, only epistemic sources can be reduced. The uncertainty taxonomy formulated for technology development that was presented in Figure 23 shows how epistemic uncertainty is further decomposed. This taxonomy provides a starting point for the types of uncertainty sources that should be targeted. The epistemic uncertainty sources can be further defined for the technology under consideration by looking at the current characterization of the technology, which is a result of past experimentation, and the desired future readiness level.

Key types of epistemic uncertainty relevant to experiment planning are *Physics Characterization*, *Device Precision*, and *Measurement Capability*. *Device Precision* is straightforward and refers to uncertainty due to the precision of the measurement devices utilized in an experiment. *Measurement Capability* uncertainty is a result of the ability, or lack of ability, to capture a phenomenon. Lastly, *Physics Characterization* includes uncertainty due to the lack of data and the quality of the data. The quality of the data is affected by the fidelity of the test article and the fidelity of the test environment.

It is observed that the quality of the data is the aspect of performance uncertinaty that is directly linked to the experimentation standards provided by the TRL morphological analysis. The other sources of epistemic uncertainty are the ones to be addressed with new experiments if the experimentation standards alone do not provide enough uncertainty reduction. Uncertainty can be reduced by selecting more precise measurement devices and through development of new measurement processes for phenomena that is difficult to capture.

The above observations, discussion, and process formulation is summarized in Figure 31. Furthermore, the proposed approach is formalized in the following hypothesis:

Hypothesis 3.3: *An understanding of the progression of experiment objectives and the sources of uncertainty that contribute to the technology impact can be used together to guide what type of phenomena should be investigated in an experiment.*

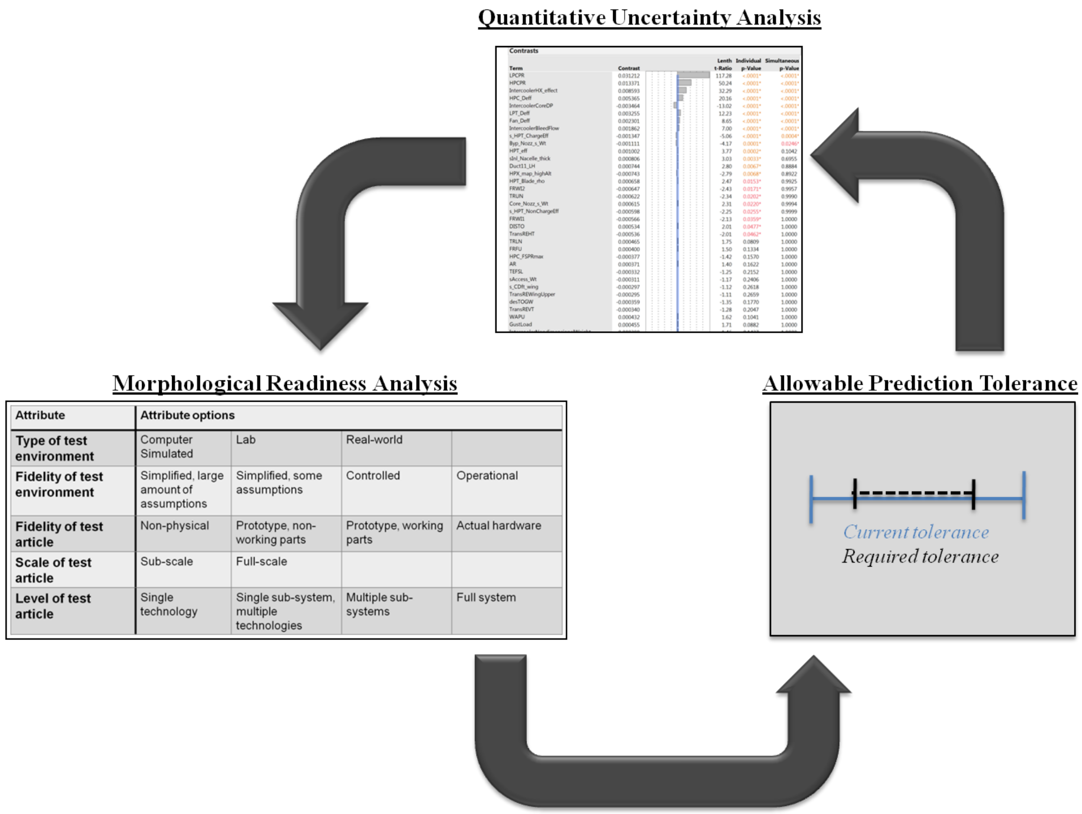

Figure 31: Proposed experiment design process.

3.4 *Technology Transition Assessment Formulation*

The fourth phase of development is *Technology Transition Assessment*. This phase addresses a single key question, which is:

- What technologies will be transitioned?

Technologies are selected for transition into system development based upon the performance capabilities they provide and their overall readiness. Therefore, the two research questions for this phase are:

Research Question 4.1: How should readiness risk of individual technologies be communicated to aid transition readiness decisions?

Research Question 4.2: How should performance risk of individual technologies be assessed and communicated to aid transition readiness decisions?

In Chapter One it was acknowledged that technologies transitioned into system development before they reach a certain level of readiness can cause an array of problems, including schedule delays, budget overruns, and undesired performance attributes. It would be expected that decision makers would select only technologies with proven performance that have reached a high level of readiness. However, to ensure the methodology developed in this research is thorough and can be utilized for many potential situations, a list of potential decision trade-offs for technology transition were defined. They are as follows:

- Technologies with potential for improved performance capabilities that have achieved a stated readiness level are transitioned.
- Technologies with potential for improved performance capabilities and low difficulty to reach the desired readiness level are transitioned.
- Technologies with potential for improved performance capabilities are transitioned, regardless of readiness risk.
- Technologies under development that have achieved a stated readiness level are transitioned, regardless of performance progression.

During this phase of development technologies will be assessed on an individual basis. This is similar to the scenarios discussed for the identification of supplemental technologies during *Technology Selection*. Therefore, previously identified metrics are relevant. For readiness, this implies decision makers will wish to know the current TRL and the difficulty that remains to reach the desired TRL. If they have already achieved the desired TRL the difficulty is no longer a factor. For performance risk, it is anticipated that decision makers would be interested in measures that quantify how effective the technology currently is at enabling performance objectives to be met and measures that quantify how much uncertainty still remains regarding its potential impact. The following hypotheses are proposed:

Hypothesis 4.1: *A risk depiction that communicates technology readiness and the expected difficulty to increase readiness will provide identification of technologies that are ready for transition and technologies that require further technology development.*

Hypothesis 4.2: *A risk depiction that includes a measure that quantifies the amount of uncertainty related to a technology impact and a measure that captures the impact a technology has on the POS of the performance objective will provide identification of technologies that provide desirable performance and should be transitioned to system development efforts.*

3.5 Risk Mitigation Formulation

Making risk-informed decisions and attempting to manage and mitigate the performance uncertainty throughout development does not guarantee that a program will meet its readiness or performance objectives due to the inherent uncertainty surrounding the information. Additionally, the information provided by this research is still subject to the decision making processes that decision makers utilize. Therefore, it is desired that this methodology can also be leveraged to address risk mitigation.

When risk is present in a program, or could be present, established risk management procedures are utilized in an attempt to control the negative effects it could cause. NASA's Continuous Risk Management(CRM) handbook states that once a risk has been identified and assessed, an entity can decide to either accept, mitigate, watch, research, elevate, or close the risk. If it is decided that the risk will be accepted or closed, then no further tracking or assessment on that particular risk will be needed because either the consequence is acceptable or the likelihood of occurrence is severely low. If it is determined that the risk should be watched or elevated, then the risk is still of a concern to the program and continual assessments will be completed on it as the program progresses. If it is decided the risk will be researched then not enough information is known at the given time to determine if it should be of concern to the program and more information will be gathered for re-assessment at a later time. Finally, if it is decided that a risk will be mitigated, new plans that deviate from the program's original plans will be put into action in an attempt to alleviate the effect the risk could have on the program.

It is important for programs that have large investments at stake to utilize some type of risk management because there will usually always be some source of uncertainty present and the exact outcomes of an investment cannot be certain. NASA's CRM procedures are an example of a formal, active risk management program; however, risk management can also be done in a passive manner. An example of passive risk management would be the utilization of robust analyses for decision making. In robust design, systems are chosen because their performance, or output, is not susceptible to variations in the input parameters. Therefore, making robust decisions would be analogous to making decisions that result in an almost certain outcome, even if the scenario is varied. This may seem like an ideal way to proceed, however, it usually cannot be utilized if the desire is to achieve a high, positive outcome. In this case, active risk management procedures would have to be utilized.

It is common practice in system development or technology development to identify potential risks before the program has begun and establish risk mitigation plans in the chance risks arise at a later time. In terms of technology development, an example of risk mitigation plans are the identification of substitute technologies to develop in case a selected technology is no longer performing well or having backup development plans (experiments) planned in case the results from the original experiments is deemed inadequate.

Pre-planning risk mitigation activities is a good practice, but is not always possible because not all potential risks can be identified in the early stages of a program. In these cases, the results from risk assessments can be analyzed for the identification of precursors. Precursors are any type of indication that the program could face a risk in the future if the development plan is executed as designed. Examples of precursors could be performance trends, budget misalignment, component delivery rates, etc. Identification of precursors have the potential to save entities time and resources.

Based upon this information, the methodology developed in this research should address how to identify a high risk situation and plan risk mitigation techniques. Therefore, the first research question to be addressed in this section is as follows:

Research Question 5.1: What information is required to identify the need for risk mitigation?

The amount of acceptable risk should decrease as technology development progresses. Therefore, as time progresses the readiness risk and performance risk of an individual technology and the technology portfolio as a whole should decrease. If the risk is re-assessed at different points throughout the lifetime of the development program, risk trends may be identified. Identified trends will either point towards risk reduction or the need for risk mitigation. Therefore, as long as the risk measures identified for tracking individual technology risk and aggregate risk at the portfolio level are adequate, the need for risk mitigation can be identified. This leads to the following hypothesis for Research Question 5.1:

Hypothesis 5.1: *Tracking the progression of a technology on the defined risk* *depictions as development progresses and the overall POS of meeting objectives will enable identification that readiness or performance objectives may not be met.*

When risk mitigation is needed, risk mitigation plans must be determined. Which leads to the following research question:

Research Question 5.2: How should risk mitigation plans be determined?

It was previously acknowledged that risk mitigation plans could be formulated at the beginning of the program or during the program when the need for risk mitigation is identified. The inclusion of Research Question 2.4 and its corresponding hypothesis provides some risk mitigation built into the process; however, the ability to plan other risk mitigation plans is also desired. When the need for risk mitigation is discovered, it could be a result of the outcome of a previous development phase. Identification of all potential risk sources was done by conducting a deductive, top-down risk analysis of the defined development process utilized for this thesis. The two potential answers for the final question, "Are the technologies ready for transition into system development?", were first identified. Next, all potential answers for previous questions were enumerated as well. The potential outcomes for each phase of development have been identified and are presented in Figure 32.

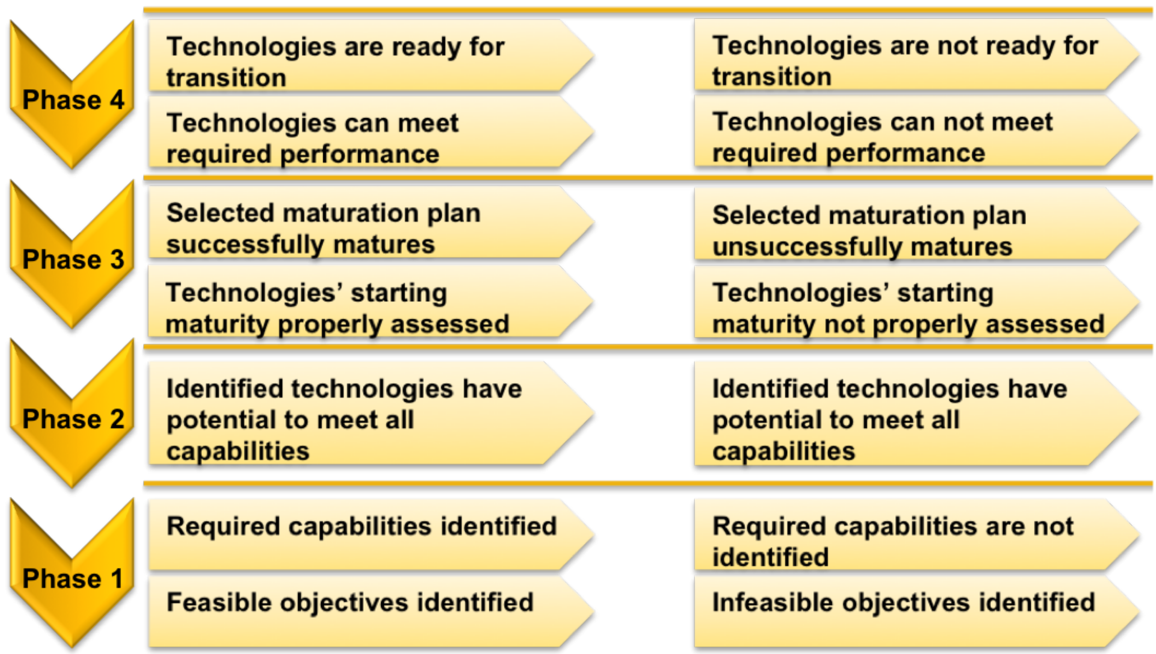

Figure 32: Potential outcomes for development process.

Development of risk mitigation plans depends on the phase that caused the risk to exist. If this can be identified, then the information provided to initially make that decision can be revisited. This information will provide the other potential decisions that could have been made at each phase of technology development. Utilization of the analysis procedures put in place could then be used to determine if the other decisions would impact either the readiness risk or performance risk of the program. Based on these observations, the following hypothesis is proposed:

Hypothesis 5.2: *Performance and readiness assessments made throughout the technology development process can be leveraged to identify the potential mitigation plans and quantify how they will affect the current risk of the program if they are implemented.*

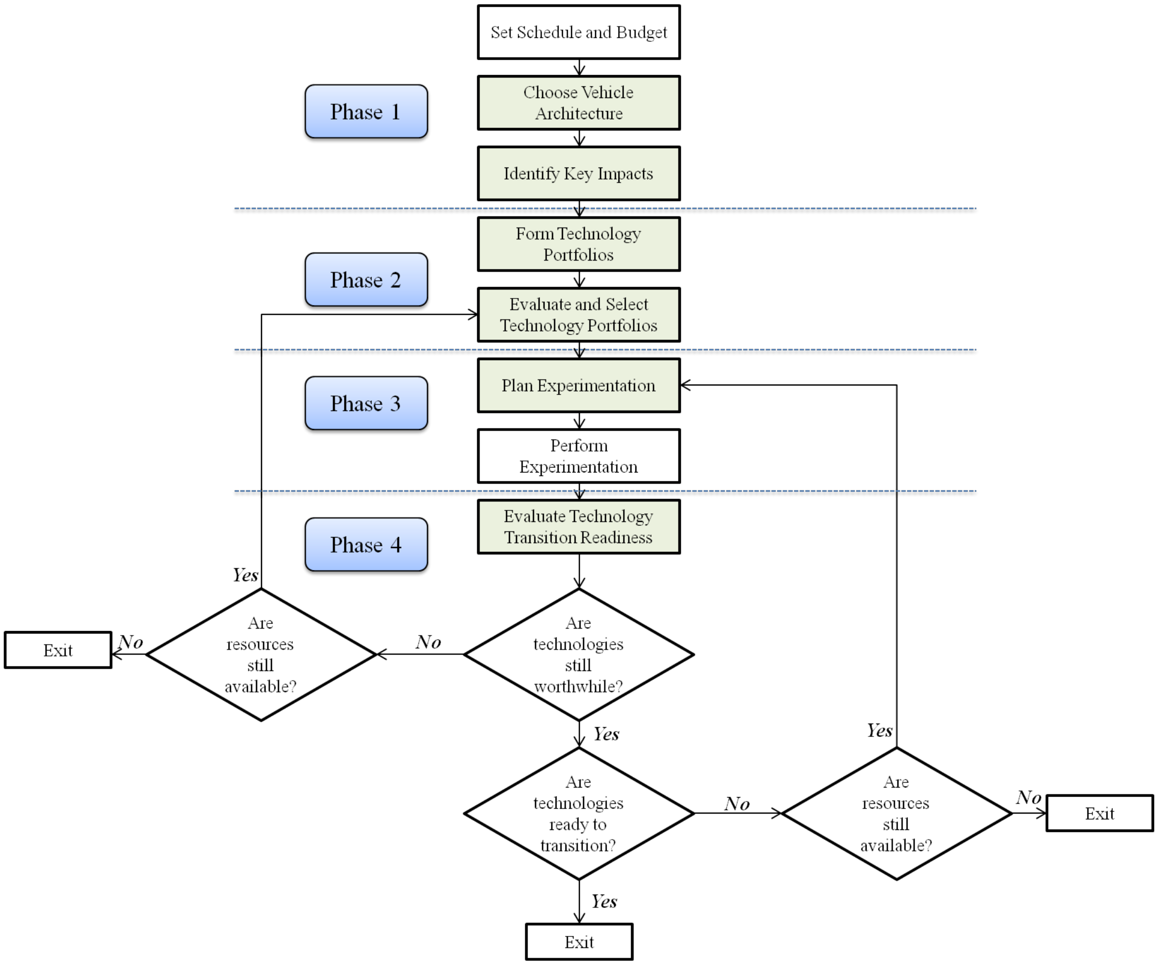

Figure 33: Process flowchart for the entire technology development methodology.

3.6 Summary of Methodology

Figure 33 provides the final outline of the main steps within the QuantUM^3 methodology. The information provided in this chapter outlines each step within the QuantUM^3 methodology and describes how risk-informed technology development decisions will be achieved. Furthermore, it was described how information resulting from the quantitative performance assessments and qualitative readiness assessments within each step of the method will be utilized to identify the need for risk mitigation.

The enumerated research questions and hypotheses were tested to provide information that can be used to either support or refute the hypotheses. The next chapter provides an outline of the experimental plan and case study. The remaining chapters provide the experiment details and results, as well as a final implmementation of the entire finalized QuantUM^3 methodology.

CHAPTER IV

EXPERIMENTAL PLAN

A set of experiments were designed to test the previously defined hypotheses. The goal of the experiments is to provide information that enables the hypotheses to either be confirmed or refuted. Therefore, the experiments map out the process that creates the required information to calculate the relevant performance risk measures and readiness risk measures. After the measures are calculated, they are assessed to determine if they sufficiently represent readiness risk and performance risk and enable the outlined technology development decisions to be made.

The analysis conducted for this thesis was divided into five different experiment sets. Each experiment set maps directly to the research questions and hypotheses defined in the previous chapter. Figure 34 shows how each experiment set maps to the different phases of the methodology that will be finalized through this research. After the completion of Experiment Sets 1-4, the entire methodology is finalized. It is then implemented in Experiment Set 5 and the prospect of risk mitigation will is explored.

Experiment Set 1 will address the key decisions in Phase One and address the relevant hypotheses. Upon completion, processes will be mapped out for architecture selection, goal setting, and the identification of important impact variables and metrics driving the objective metrics. In Experiment Set 2, a processes for how to formulate potential technology portfolios and then analyze them with respect to the proposed risk measures will be enumerated. Experiment Set 3 will outline and test a process for measuring and communicating technology readiness. This process will then be utilized, along with other processes, to form and test an experiment planning method. Experiment Set 4 will then outline the necessary steps for determining if a technology is ready for transition. Finally, Experiment Set 5 will synthesize the results from the previous experiment sets to form the final proposed methodology and test its integrated capabilities on one last example.

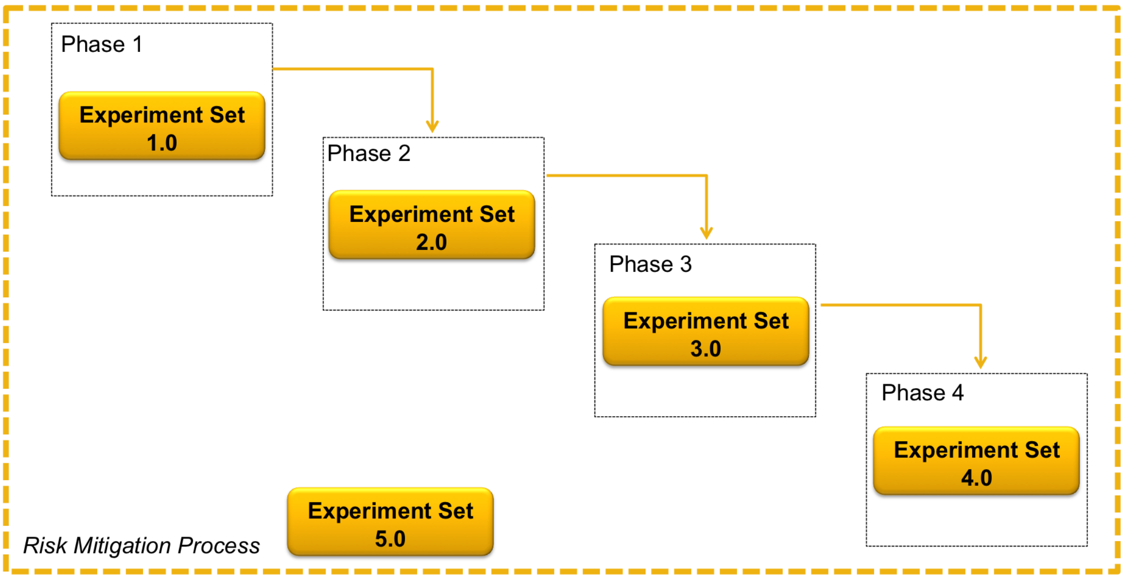

Figure 34: Experimental plan for testing hypotheses and defining the final methodology.

Formulation of the experimental plan requires the definition of a case study and a relevant modeling environment. The case study will provide context for the assessment in terms of objective metrics and the modeling environment provides the means to calculate the identified metrics. A relevant case study to the current state of the aerospace industry was desired, and background research led to the identification of environmental impacts of aviation and programs in place to address it. The following section will provide relevant information on this case study definition. The rest of the chapter will then focus on the defining the required modeling efforts and the available tools

4.1 Environmental Motivation for the Aircraft Industry

Recently the aerospace industry is centered on goals related to diminished environmental impact. The motivation for this shift comes from a variety of statistics dealing with projected air travel growth [18] [12], increased fuel prices [103] [18], atmospheric emissions effects [12] [103] [62], and community noise concerns [25].The air travel environmental problem has been acknowledged by government entities and plans have been put in place to undertake them. In 2010, the National Aeronautics Research and Development Plan (NARDP) listed as two of its goals “Advance development of technologies and operations to enable significant increases in the energy efficiency of the aviation system” and “Advance development of technologies and operational procedures to decrease the significant environmental impacts of the aviation system”[10]. For each of these broad goals, specific detailed goals for near term (2015, or N+1), mid term (2020, or N+2), and far term (2025, or N+3) time frames were enumerated to help guide research plans.

The FAA and NASA have responded to these goals by forming three separate technology research and development programs aimed at targeting each of the three time frames laid forth by the NARDP. The FAAs Continuous Lower Energy, Emissions and Noise (CLEEN) project is focused on maturing promising energy efficient, clean and quite technologies for the N+1 timeframe[42]. The NASA Environmentally Responsible Aviation (ERA) project is focused on conducting research at the system level on concepts and technologies that potentially could assist in meeting the N+2 time frame environmental goals[115] . Similarly, the NASA Fixed Wing (FW) program, formerly known as the subsonic fixed wing (SFW) program, is focused on developing advanced vehicle concepts and technologies that fall under the N+3 timeframe. Figure 35 displays the goals for each of these timeframes.

The goals for the NASA ERA project are to facilitate the reduction of fuel burn by 50 percent relative to best in class, community noise by 42dB below stage 4, and

	TECHNOLOGY GENERATIONS (Technology Readiness Level = 4-6)		
TECHNOLOGY BENEFITS*	N+1 (2015)	N+2 (2020**)	N+3 (2025)
Noise (cum below Stage 4)	- 32 dB	- 42 dB	- 71 dB
LTO NOx Emissions (below CAEP 6)	-60%	-75%	-80%
Cruise NOx Emissions (rel. to 2005 best in class)	-55%	-70%	-80%
Aircraft Fuel/Energy Consumption‡ (rel. to 2005 best in class)	-33%	-50%	-60%

* Projected benefits once technologies are matured and implemented by industry. Benefits vary by vehicle size and mission; N+1 and N+3 values are referenced to a 737-800 with CFM56-7B engines, N+2 values are referenced to a 777-200 with GE90 engines

** ERA's time phased approach includes advancing "long-pole" technologies to TRL 6 by 2015

‡ CO_2 emission benefits dependent on life-cycle CO_{2e} per MJ for fuel and/or energy source used

Figure 35: Environmental goals for N+1, N+2, and N+3 timeframe.

NOx emissions by 70 percent at cruise by increasing the TRL of a set of technologies to TRL 6 by 2020. Phase 1 of ERA identified, evaluated, and selected promising technologies and advanced vehicle concepts. The potential impacts of each of the identified technologies were characterized and then down-selected into a smaller subset based off of the performance assessment and other factors.

Phase 2 of ERA is focused around the research and development of the smaller technology subset. Eight technologies were down-selected, and an experimentation plan to increase the TRL for each was proposed. The technologies and their experimentation plans are referred to as the Integrated Technology Demonstrations(ITDs). The purpose of the ITDs is to mature the technologies and track the performance progression as the uncertainty around their predicted benefit is reduced.

The ERA program provides an ideal test problem for this research because it is a technology development program with focused system-level objectives, identified system architectures, and technologies that map to a variety of different disciplines within the aircraft. Additionally, a working relationship with the NASA ERA program has been established, and information about the technology impacts and the experimental plans is readily available. Therefore, the NASA ERA program will be used to frame the experiments conducted within this thesis.

4.2 Relevant Physics to be Captured

4.2.1 Aircraft Design

In order to capture the performance of an advanced system, such as an entire aircraft system, many different disciplines must be represented, integrated, and synthesized. Conceptual aircraft design involves a process called sizing and synthesis. During sizing and synthesis relevant characteristics are calculated for each aircraft performance discipline and the resulting information is used to scale the overall aircraft. Information from one discipline may be required to calculate the metrics of a different discipline, so several feedback and feed-forward loops may be required.

During vehicle sizing and synthesis, the characteristics that define the aircraft system are calculated. First, the performance requirements of the aircraft are defined through a mission profile and other supporting information. Next, the geometric parameters of the aircraft are defined and the resulting metrics for each relevant discipline are calculated. After this is complete, the aircraft is sized according to the mission profile. Iterations of this process are conducted until it converges on a final aircraft system design that meets all of the requirements.

Figure 36 displays a sizing and synthesis process be used for aircraft design and analysis. Some key aircraft disciplines are: aerodynamics, structures, stability and control, propulsion, manufacturing, performance, safety, and economics. The tools used during this phase of design and analysis would be high fidelity tools, such as physics-based design tools.

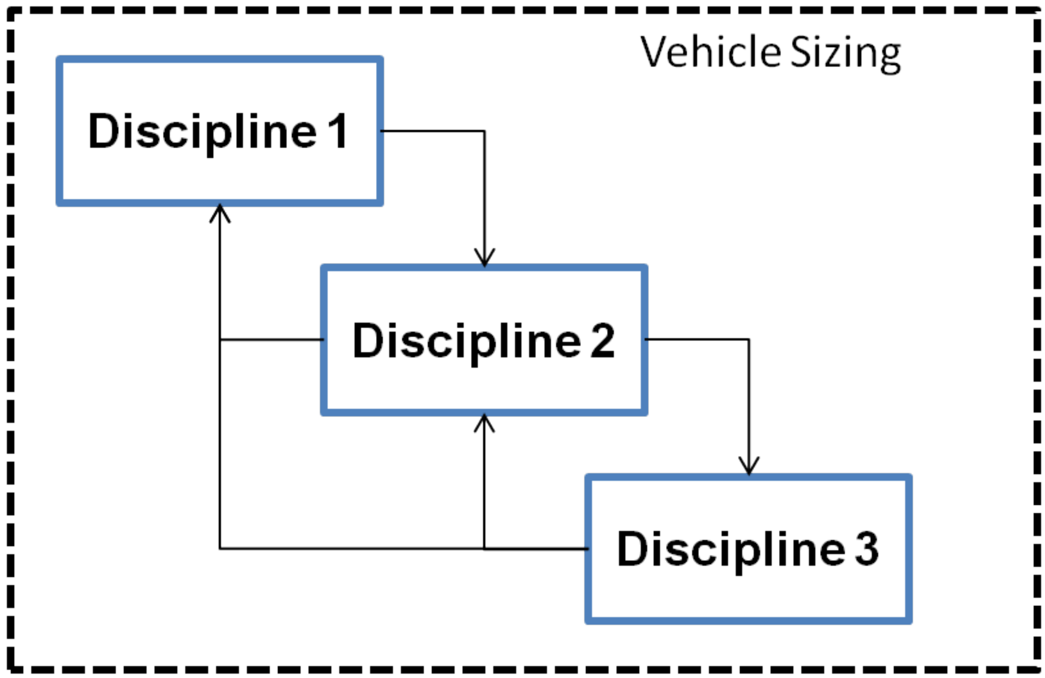

Figure 36: Sizing and synthesis process for aircraft conceptual design.

Based on this process and the information communicated through Figure 36, a multi-disciplinary, physics-based aircraft design and analysis environment is required in order to provide adequate system level assessments. The design tool should include a user-defined mission profile that can be used to size the vehicle, disciplinary tools necessary to capture the performance of the vehicle, and geometric parameters that define the shape of the system.

A Figure 36 displays, there are many different aircraft performance disciplines that could be represented in a multidisciplinary tool. When building or selecting a design tool, it is important to know what disciplines must be represented to ensure the proper tools are being used. Therefore, the required characteristics and metrics for the problem at hand must be defined.

The motivating environmental problem utilized for this research requires the calculation of three main objective metrics: vehicle fuel burn, LTO NOx emissions, and vehicle noise. These objective metrics have been dissected to identify the type of supporting information that is required for their calculation. This decomposition enabled the identification of key aircraft disciplines that must be included in the physics-based design tool utilized for this research. The following sub-sections provide the results of this analysis.

4.2.2 Fuel Burn

Vehicle fuel burn is defined by the block fuel. Block fuel is the amount of fuel utilized by an aircraft during a mission from the time the engine is turned on to the time the engine is shut off. Therefore, the mission the aircraft flies is a main driver in the block fuel value. For a commercial aircraft, the mission profile consists of take-off, climb, cruise, descent, and landing. The largest portion of the mission is cruise. Therefore, the fuel used during cruise is representative of the total fuel used for the mission.

Equation 24 provides the Breguet range equation, which enables the calculation of the maximum range for a specified aircraft and a given amount of fuel. In this context the aircraft is defined by the lift-to-drag ratio $\frac{C_L}{C_D}$, the thrust specific fuel consumption $TSFC$, and the weight fraction. In the weight fraction, W_0 is the weight before cruise and W_1 is the weight after cruise. Therefore, the difference in W_0 and W_1 is the weight of the fuel consumed during cruise.[84]

$$Range = \frac{V}{TSFC}\frac{C_L}{C_D} ln\frac{W_0}{W_1} \tag{24}$$

The Breguet range equation can be rearranged to provide the weight of the fuel consumed during cruise as a function of the cruise range and defining aircraft characteristics. Equation 25 provides this rearrangement. This function enables the calculation of the fuel weight for a fixed range mission. Based on previous observations, the resulting fuel weight calculated by Equation 25 can be used as a surrogate for block fuel.

$$W_{fuel} = [W_{empty} + W_{payload}]$$
$$\left[exp\left(\frac{Range * TSFC}{V} * \frac{D}{L}\right) - 1\right] \tag{25}$$

Once the block fuel is calculated, the fuel burn reduction can be determined. Calculation of fuel burn reduction requires a block fuel value baseline value. The baseline value is the calculated block fuel for a defined baseline vehicle of similar size and mission profile. Equation 26 provides the manner in which fuel burn reduction would be calculated.

$$FuelBurnReduction = \frac{W_{fuel_{baseline}} - W_{fuel_{new}}}{W_{fuel_{baseline}}} \tag{26}$$

Equation 25 provides the necessary information to identify the disciplines that must be represented to calculated fuel burn reduction. As mentioned, block fuel is a function of a key aerodynamic characteristic, lift-to-drag ratio, a key propulsion characteristics $TSFC$, and vehicle weight information. Therefore, the analysis code utilized for this research must include the disciplines of aerodynamics and propulsion and have the ability to calculate the weight of the aircraft.

4.2.3 NOx Emissions

Calculating NOx emissions is complex and requires information regarding the design of the engine's combustor. Methods have been developed that aim to correlate combustor NOx emissions with engine operating conditions. Commonly, these methods rely on the effect of the combustor inlet pressure and temperature.[2]

One such correlation method has been deemed the P3T3 method. The P3T3 method corrects NOx emissions index (EINOx) measurements taken during certification testing to the altitude condition based upon the knowledge of the combustor operating conditions at sea level and altitude. The altitude corrections are applied to NOx for inlet pressure, fuel-to-air ratio (FAR), and humidity. Implementation of this method requires detailed engine data which is usually proprietary and only available to the engine manufacturer.[2]

Other simplified methods exist which do not require the sensitive engine information. One such example is a set of fuel flow correlation methods that use the fact that higher pressures and temperatures mean higher fuel flow, and result in increased EINOx. There is general agreement in the performance of simplified fuel flow correlation methods with P3T3 methods.[2]

Rules for NOx emissions are governed by the International Civil Aviation Organization (ICAO). ICAO's Committee on Aviation and Environmental Protection (CAEP) developed international standards EPA adopted emission standards for engines with rated thrusts greater than 26.7 kilonewtons which were previously adopted by ICAO. There are two new tiers of stringent emissions standards for oxides of nitrogen (NOx), Tier 6 and Tier 8 standards. Application of Tier 6 standards, which will be referred to as CAEP 6, depends on the date the engine model received its original type certificate.[11] The rules are as follows:

- Engine models originally certified prior to the effective date of the rule do not have to comply to CAEP 6 through 2012. After 2012, they must comply with CAEP 6.
- Engine models originally certified between effective date of the rule and end of 2013 must meet CAEP 6.
- Engine models originally certified beginning on or after January 1, 2014 must meet CAEP 8 rules

The CAEP 6 rule for each engine is provided in units of grams/kilonewton and calculated as follows:

- If the engine's overall pressure ratio (OPR) is less than or equal to 30:

$$NOx = 16.72 + (1.408 * OPR) \tag{27}$$

- If the engine's OPR is greater than 30 but less than 82.6:

$$NOx = -1.04 + (2.0 * OPR) \tag{28}$$

- If the engine's OPR is greater than or equal to 82.6:

$$NOx = -32 + (1.6 * OPR) \tag{29}$$

Figure 37 displays the procedure followed for ICAO certification. The correlation equation used in this method is repeated in Equation 30. In this equation SLS,ISA stands for sea level static altitude and an International Standard Atmosphere day conditions, h is the measured humidity, and n and m are the corrections for combustor inlet pressure and FAR, respectively.

$$EINOx_{SLS,ISA} = EINOx \left(\frac{P_{SLS,ISA}}{P}\right)^{n} \left(\frac{FAR_{SLS,ISA}}{FAR}\right)^{m} \exp\left[19(h - 0.00629)\right] \tag{30}$$

Equation 30 provides relevant information that enables the identification of the disciplines that must be represented to calculate NOx emissions. Information on the aircraft engine, specifically the combustor, are required. Furthermore, information on the operating conditions, such as altitude, is also required. Therefore, the calculation of NOx emissions requires more detailed propulsion modeling than the calculation of fuel burn reduction requires.

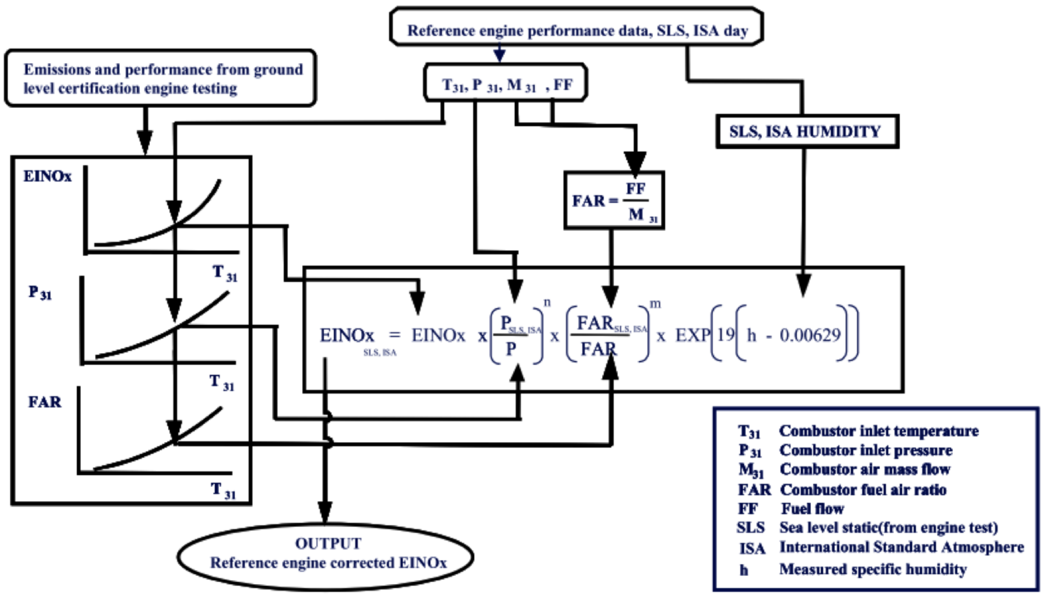

Figure 37: ICAO Annex 16 Volume II NOx Emissions Correction Scheme[2]

4.2.4 Noise

The first aircraft noise regulations were put in place by the FAA in 1969 in Title 14, Code of Federal Regulations (14 CFR) part 36. It set a noise emissions limit for large aircraft by setting Stage 2 certification limits for new aircraft designs. In 1977 part 36 was amended by the FAA to divide aircraft noise levels into three specific stages. Individual limits were set for each of the three defined phases, and these new limits were titled Stage 3 limits.[3] The limits are provided in unites of decibels and are divided into three segments of flight: cutback, sideline, and approach.

The limits are defined as follows:

- Cutback:
  - If the aircraft takeoff gross weight (TOGW) is greater than or equal to 850,000 pounds, the Stage 3 cutback limit is 101 dB
  - if the aircraft TOGW is less than or equal to 106,250 pounds, the Stage 3 cutback limit is 89 dB

- If the aircraft TOGW is between 106,250 pounds and 850,000 pounds, the Stage 3 cutback limit is calculated as:

$$Cutback = 89 + 4 * \left[\frac{log\left(\frac{TOGW}{106250}\right)}{log(2)} \right] \tag{31}$$

- Sideline:
  - If the aircraft TOGW is greater than or equal to 882,000 pounds, the Stage 3 sideline limit is 103 dB
  - If the aircraft TOGW is less than or equal to 77,200 pounds, the Stage 3 sideline limit is 94 dB
  - If the aircraft TOGW is between 77,200 pounds and 882,000 pounds, the Stage 3 sideline limit is calculated as:

$$Sideline = 94 + 2.56 * \left[\frac{log\left(\frac{TOGW}{77200}\right)}{log(2)} \right] \tag{32}$$

- Approach:
  - If the aircraft TOGW is greater than or equal to 617,300 pounds, the Stage 3 approach limit is 105 dB
  - If the aircraft TOGW is less than or to 77,200 pounds, the Stage 3 approach limit is 98 dB
  - If the aircraft TOGW is between 77,200 pounds and 617,300 pounds, the Stage 3 approach limit is calculated as:

$$Approach = 98 + 2.33 * \left[\frac{log\left(\frac{TOGW}{77200}\right)}{log(2)} \right] \tag{33}$$

The FAA adopted new noise standards in 2005 for subsonic jet airplanes. The noise standard is labeled Stage 4 and applies to any new airplane type design application submitted on or after January 1, 2006. The Stage 4 standard was developed by the international community through ICAO's CAEP.[4] The Stage 4 cumulative noise limit is defined as the sum of the three Phase 3 limits (cutback, sideline, and approach) reduced by 10 dB.

Calculation of noise characteristics is a bit of an art, but it is a function of the aircraft geometry, aircraft weight, and engine properties. Noise produced by an aircraft can be divided into noise from the airframe, or overall configuration, and noise from the engine. The equations provided to calculate the Stage 3 noise limits imply that noise is correlated to the TOGW of the aircraft. Therefore, it is important that the environment utilized for this research has a sizing component that enables the calculation of the total weight. Furthermore, it was discovered that noise created by the engine is correlated to the jet speed coming out of the propulsor.

After further investigation into noise calculations, it was determined that an analysis code solely dedicated to analyzing noise is required. It is likely a noise analysis code will require aircraft geometry characteristics, propulsion information, and aerodynamics information.

4.3 Experimental Test Bed: Environmental Design Space

Based on the problem formulation and research objective for this thesis, a computational modeling and simulation environment that meets the following characteristics is required:

- It is a physics-based formulation
- It can facilitate uncertainty propagation
- It provides system level responses as a function of lower level system components
- It provides the ability to capture technology impacts
- Captures the following disciplines:

  - Vehicle sizing
  - Aerodynamics
  - Propulsion
  - NOx correlations
  - Noise

Furthermore, it is desired to operate on an environment that has gone through a validation process to ensure the it creates defensible results that are believable. Lastly, the identified environment must be readily accessible.

The Environmental Design Space (EDS) is a modeling and simulation environment developed for the Federal Aviation Administration(FAA) Partnership for Air Transportation Noise and Emissions Reduction (PARTNER) Center of Excellence. It is based on well-established NASA modules.[54] EDS was developed to meet the following set of characteristics[56]:

- Transparency: EDS should be open, available, and transparent in concept and execution.
- Flexibility: EDS should have flexibility to adapt to and accept future modifications, be able to respond to changing future needs, and be able to access future technologies and new functionality. It should also be modular and flexible, to allow users to incorporate other tools.
- Uncertainty: EDS should be able to manage uncertainties within its modeling capacity.
- Predictive: EDS should have a predictive capability as part of its functionality.
- Availability: EDS inputs must be non-proprietary.
- Coordination: EDS must be able to interface with the other FAA tools.

- Interaction: EDS should be developed with active stakeholder involvement.
- Validation: EDS development process should include a validation plan that involves input from a variety of stakeholders by promoting industry collaboration and incorporating industry feedback.

Each of the tools within EDS are physics-based formulations, and altogether they enable the assessment of source noise, exhaust emissions, and performance of both current aircraft vehicle systems and future aircraft systems with new, emerging technologies.[99]. Additionally the integrated aspect of EDS enables analysis of the system interdependencies and design trade-offs. The modules within EDS are:

- **Numerical Propulsion System Simulation (NPSS)**
- **Compressor Map Generator (CMPGEN)**
- **Weight Analysis of Turbine Engines (WATE)**
- **Flight Optimization System (FLOPS)**
- **Pressure and Temperature Correlations (P3T3)**
- **Aircraft Noise Prediction Program (ANOPP)**

The EDS modules are integrated through the object-oriented NPSS coding language to enable automated information passing. Figure 38 displays how the information flows within the environment.

EDS has been validated and calibrated using existing vehicle data for a wide variety of aircraft architectures and seat classes. Its capabilities have been proven through its application to various assessments for NASA, the FAA, and academia. The results of many of these studies have been presented at various conferences and published in leading aerospace journals[29, 36, 38, 45, 47, 48, 52, 53, 74, 81, 79, 80, 82, 83, 92, 100, 101].

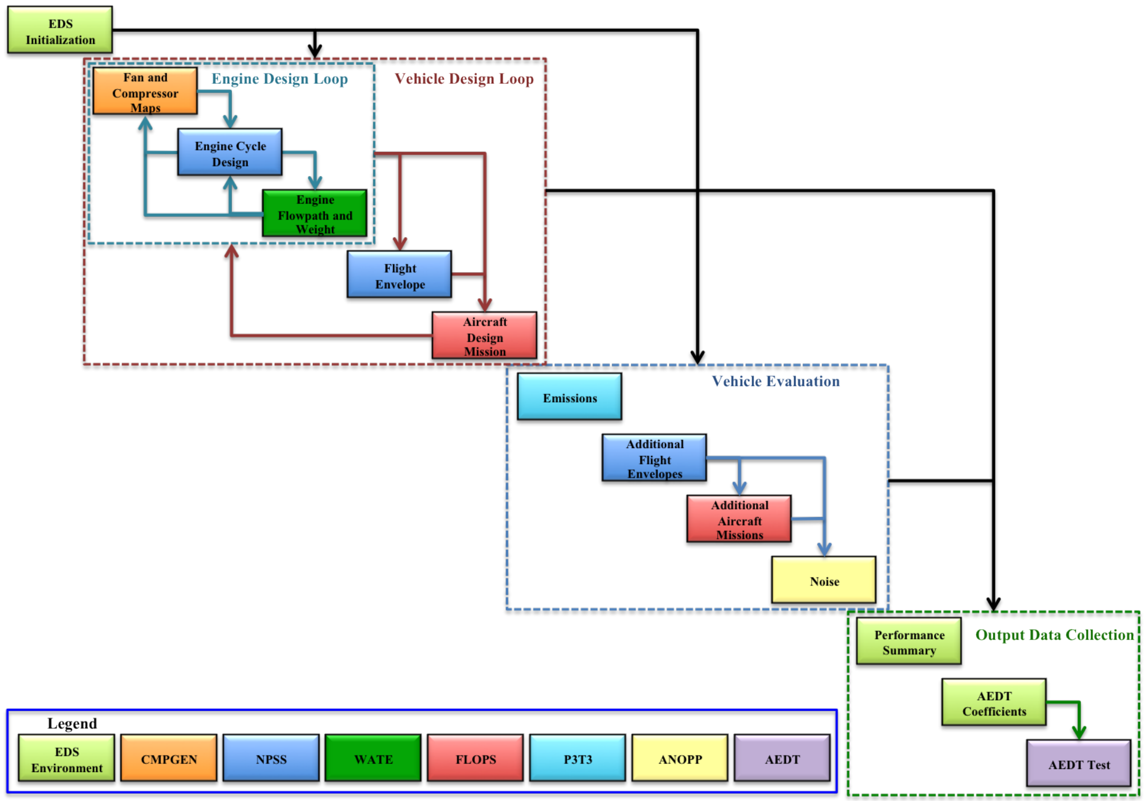

Figure 38: Environmental Design Space.

EDS provides all of the capabilities required to complete the assessments for this thesis. Additionally, the environment resides within the Aerospace Systems Design Lab at the Georgia Institute of Technology; therefore, it is readily available. Based on these observations, EDS will be the modeling environment used to facilitate the experimentation required for this research. The following sub-sections will provide more information on the different modules EDS includes.

4.3.1 EDS Modules

4.3.1.1 Numerical Propulsion System Simulation (NPSS)

NPSS was developed through a cooperative effort between NASA and other government agencies, industry, and universities. It is an analysis code that is focused on large-scale modeling of complete aircraft engines.[63] NPSS is capable of analyzing both on-design and off-design engine performance.[102] NPSS was developed using an object-oriented programming language that was adapted for the integration of EDS modules. The cycle analysis is completed using the built-in Newton-Rhapson solver that can handled constrained solutions.

4.3.1.2 Compressor Map Generator (CMPGEN)

CMPGEN is an axial compressor map generator that is based on empirical characteristics related to the overall performance requirements.[37]

4.3.1.3 Weight Analysis of Turbine Engines (WATE)

WATE was developed by Boeing in cooperation with NASA. It is capable of calculating the weight of different components that make up the aircraft engine and the flowpaths. Thermodynamic data is input into WATE and transformed into mechanical design variables for the engine that enable the flowpath and weight calculations.

4.3.1.4 Flight Optimization System (FLOPS)

FLOPS is a program developed by NASA that is used for conceptual and preliminary design of aircraft systems. It is a multidisciplinary analysis code that has nine primary modules: weights, aerodynamics, engine cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis, and program control. EDS primarily utilizes the aerodynamics module for performance analysis and mission analysis module for vehicle sizing. Some aspects of the other modules are used and some are replaced by the other tools included in EDS.

The aerodynamics module utilizes a modified version of the empirical drag estimation technique (EDET). The output of this module is drag polars. The mission performance module uses weight information, aerodynamic information, and propulsion information to calculate the performance for design mission. The mission is defined by the different segments of the mission profile.[71]

4.3.1.5 Pressure and Temperature Correlations (P3T3)

The P3T3 module utilizes the previously discussed correlation equations for the calculation of NOx emissions. The correlations are built from the data in the ICAO database of existing combustors. THerefore, the correlations are not necessarily relevant for future, advanced combustors. Work has been conducted to augment the P3T3 correlations for advanced concepts and the P3T3 EDS module is regularly updated.[101]

4.3.1.6 Aircraft Noise Prediction Program (ANOPP)

ANOPP was created by NASA to predict the total aircraft noise signature from propulsion and airframe noise sources. The prediction methods within ANOPP are empirical or semi-empirical models that use the best available experimental data sets and acoustic prediction methods. The prediction methods within ANOPP are relevant for conventional aircraft configurations, but corrections are required for non-conventional configurations. Recently, work has been published on updating ANOPP to include more fidelity that will enable its use on unconventional configurations. This newly developed code is ANOPP2.

4.3.2 Relevant Vehicle Models

EDS is capable of analyzing aircraft concepts of varying seat class and configurations. The most common aircraft configuration is the tube and wing concept. Currently, there are eight different tube and wing models that EDS can analyze, ranging from a 50 passenger regional jet to a 400 passenger quad-engine aircraft. Furthermore, it can analyze hybrid-wing body (HWB) concepts, double-bubble concepts, and over-the-wing engine concepts.

Each aircraft model is defined by geometric variables and relevant aerodynamic and propulsion characteristics. The models are calibrated to existing aircraft systems by matching key performance attributes through the augmentation of input variables.

Furthermore, each aircraft model has a corresponding design mission that is used for sizing purposes. This means each vehicle is optimized according to the input mission profile.

This research investigate two main seat classes: a 150 passenger large single aisle (LSA) aircraft and a 300 passenger large twin aisle (LTA) aircraft. The LSA aircraft will be a tube and wing configuration, whereas both tube and wing and HWB concepts for the LTA will be utilized. Characteristics of the design mission for the LSA vehicle are provided in Table 7 and the LTA vehicles in Table 8.

Table 7: 150 passenger LSA aircraft design mission

Characteristics	Value
Take-off time	0.6 min
Taxi-out time	9.0 min
Taxi-in time	5.0 min
Cruise Mach number	0.79
Cruise altitude	41,000 ft
Mission range	2,950 nmi

Table 8: 300 passenger LSA aircraft design mission for tube and wing and HWB

Characteristics	Value
Take-off time	0.6 min
Taxi-out time	9.0 min
Taxi-in time	5.0 min
Cruise Mach number	0.84
Cruise altitude	43,000 ft
Mission range	7,440 nmi

CHAPTER V

INVESTIGATION OF GOAL SETTING AND TECHNOLOGY SELECTION

5.1 Examination of Phase 1

The objective of Experiment Set 1 is to test Hypothesis 1.1, Hypothesis 1.2, and Hypothesis 1.3 by formulating and implementing the processes for *Choose Vehicle Architecture* and *Identify Key Impacts*. Recall, the goal of this phase is to identify the important impacts that are driving the performance relative to the goal metrics through the utilization of a modeling environment, sensitivity analysis, and technology impact forecasting. Each step within the processes are outlined and implemented through the following sub-sections.

5.1.1 Vehicle Architecture Selection

The first step in technology development captured by this research is to select the vehicle architecture. Figure 39 shows the process mapped out for the selection of vehicle architectures. First, a deterministic assessment is conducted on the baseline architectures under consideration. Next, impacts that are expected to improve in the future are identified and utilized for a probabilistic assessment of the architectures. The results of the probabilistic assessment are then combined with other non-performance characteristics of the architectures to facilitate the selection of the vehicle architecture based upon the provided decision scenario.

This process was tested by first identifying an analysis tool that links the system level performance of an aircraft vehicle to lower level metrics is required to provide performance analysis. As previously discussed in Chapter Four, the EDS modeling

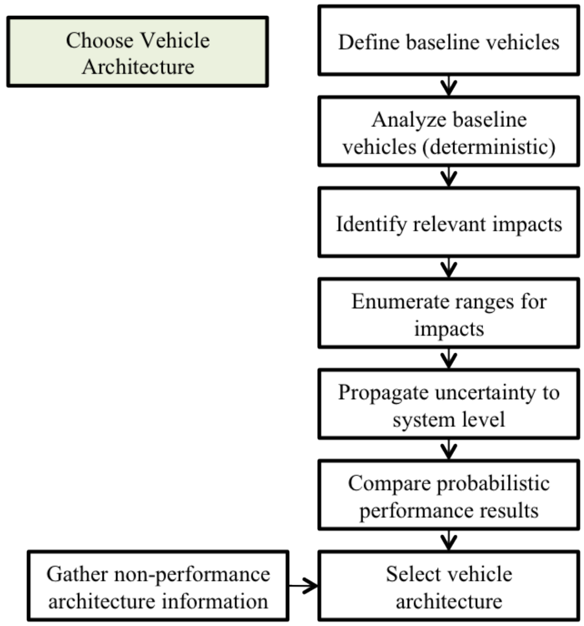

Figure 39: Process flowchart for vehicle architecture selection.

environment fulfills these requirements. Furthermore, three different vehicle models are available for baseline vehicle architectures: a single aisle tube and wing aircraft (LSA), a twin aisle tube and wing aircraft (LTA), and a twin aisle HWB aircraft (HWB). These vehicles are utilized as the architecture alternatives under consideration for the development program.

Two different sets of baselines were examined for each aircraft. The first baseline is considered representative of a 1995-era aircraft. Performance results of these vehicles are displayed in Table 9. Note that results for only two baseline vehicles are presented, the LSA and the LTA. There is no representative 1995 HWB baseline because the HWB aircraft configuration was not operational during that timeframe.

Table 9 displays performance values for takeoff gross weight (TOGW) in pounds, block fuel in pounds, noise margin relative to the Chapter Four noise rule in decibels, and the percentage LT) NOx reduction below the CAEP 6 rule. Note that while the LTA vehicle has a predictably larger TOGW and block fuel and correspondingly lower NOx reduction, it shows a greater noise margin. The values listed in this table for block fuel will be used throughout the rest of this research for calculation of percentage fuel burn reduction.

Table 9: 1995 baseline vehicle performance for large single aisle and large twin aisle tube and wing aircraft

Responses	LSA	LTA
Takeoff Gross Weight (lbs)	170,012	615,789
Block Fuel (lbs)	36,099	234,345
Noise Margin	4.12	8.26
LTO NOx below CAEP 6 (%)	40.78	29.01

A second set of baseline vehicles were modeled that represent the current state of the art. These aircraft vehicles are representative of 2010-era LSA, LTA, and HWB aircraft. For the 2010 LSA and LTA vehicles, the models were created by adding a set of new technologies to the existing 1995 baseline vehicles. For the 2010 HWB vehicle, a new vehicle model was created that includes the same new set of technologies. The technologies included in this set will be referred to as the 2010 baseline technologies and are displayed in Table 10. The technologies are incorporated into the vehicles by utilizing the previously discussed technology k-factor modeling approach. Since each of the 2010 baseline technologies are currently operational, it is assumed that they have reached a TRL of 9 and they are characterized by a set of deterministic impacts. Therefore, the addition of these technologies does not add any performance uncertainty or readiness risk. Furthermore, a geared fan (GF) engine architecture is utilized for each of the three vehicle 2010 vehicle architectures.

Table 10: Technologies included on 2010 baseline vehicles

Technology Identifier	Technology Name
T1	Composite Technologies
T4	Gust Load Alleviation
T9	Excrescence Reduction
T27.1A	Advanced TBC Coatings - HPT Blade
T27.2A	Advanced TBC Coatings - HPT Vane
T27.3A	Advanced TBC Coatings - LPT Blade
T27.4A	Advanced TBC Coatings - LPT Vane
T36.1	Polymer Matrix Composites (PMC) - Nacelles
T36.2	Polymer Matrix Composites (PMC) - Fan Case
T36.3 + T38	Polymer Matrix Composites (PMC) - Fan Stator
T36.4	Polymer Matrix Composites (PMC) - Bypass Duct
T37	PMC Fan Blade with Metal Leading Edge
T43	Aft Cowl Liners
T45	Combustor Noise Plug Liner
T46	Fixed Geometry Core Chevrons
T60	Zero Splice Inlet
T92	Blisk
T93.1	Ti-Al - LPT Stator
T93.3	Ti-Al - LPT Aft Blades

Table 11 provides performance values for takeoff gross weight (TOGW), block fuel, the noise margin relative to Chapter Four noise rule in decibels, and the percentage LTA NOx reduction below the CAEP 6 rule. Additionally, 11 provides values for percentage fuel burn reduction relative to the 1995 baseline block fuel values. Again, the LTA has greater values for TOGW, block fuel, and noise margin and a lower NOx reduction. Now, however, the impact of the HWB vehicle configuration is recognized by comparing its performance with the performance of the LTA since they are vehicles of the same seat class. The HWB provides an improved TOGW, block fuel, and noise margin. The LTA provides marginally better performance with respect to NOx reduction. For fuel burn reduction, the HWB provides the best performance with the LTA coming in second and the LSA last.

Table 11: 2010 baseline vehicle performance for large single aisle and large twin aisle tube and wing aircraft and large twin aisle hybrid wing body aircraft

Responses	LSA	LTA	HWB
Takeoff Gross Weight (lbs)	159,570	554,020	536,550
Block Fuel (lbs)	30,981	198,480	179,410
Fuel Burn Reduction (%)	14.18	15.30	23.44
Noise Margin	22.62	24.63	40.09
LTO NOx below CAEP 6 (%)	44.90	53.14	52.67

Selection of a vehicle architecture can be done based upon the deterministic 2010 baseline results. However, it was hypothesized that a probabilistic assessment could provide knowledge of how the vehicles might perform in the future with the addition of technologies that add incremental performance benefits. The process provided in Figure 39 involves technology impact forecasting and probabilistic analysis was formulated and performed for each of the three vehicles to produce probabilistic performance results. The designs of the vehicles have been frozen to the 2010 baseline configurations; however, the technology impact design space can now be opened through the use of the technology k-factors. In this context, the TIF analysis is a bounding exercise that enables the identification of the future performance of the vehicles.

The first step of the TIF process was to identify the technology k-factors within the EDS environment that are relevant to each of the objective metrics. For the rest of this assessment only the LTA system and HWB system are considered because they are of similar seat classes. A total of 56 lower-level input variables captured by the EDS environment were identified for the LTA vehicle and 48 for the HWB vehicle. The values for the k-factors are no longer set to their deterministic values from the 2010 baseline vehicles. Instead, they are now probabilistic variables because their exact future values are unknown. The ranges for each of the k-factors can be set by conducting background research or utilizing SME-input. For this experiment, the ranges were based upon the known operational limits of the EDS environment and SME-input on realistic improvements. Next, a space filling design of experiment (DOE) was formulated for the ranges of the variables.

The simulations defined by the DOE were performed and the relevant outputs for each case were recorded. This process was then repeated for each of the three vehicles and the results are shown in Figure 40 through a scatterplot matrix. Plotted in the scatterplot matrix are the three objectives against each other. The red points represent the LTA probabilistic assessment and the blue points represent the HWB probabilistic assessment. An immediate observation is the performance benefit provided by the HWB for noise margin. For fuel burn reduction, it appears the HWB marginally has the ability to provide the best improvement and the performance. Lastly, the performance for NOx emissions is relatively similar for both vehicles.

The results of the probabilistic analysis provide the type of performance that can be expected of these next generation aircraft system architectures. The black lines represent the performance goals set for the ERA program from Figure 35. One important note to make is that the uncertainty captured in this probablistic assessment is only related to the uncertain technology capabilities that will be available in the future. Therefore, no other sources of uncertainty, such as vehicle design uncertainty, is captured. Figure 40 may be a misleading uncertainty representation, and therefore

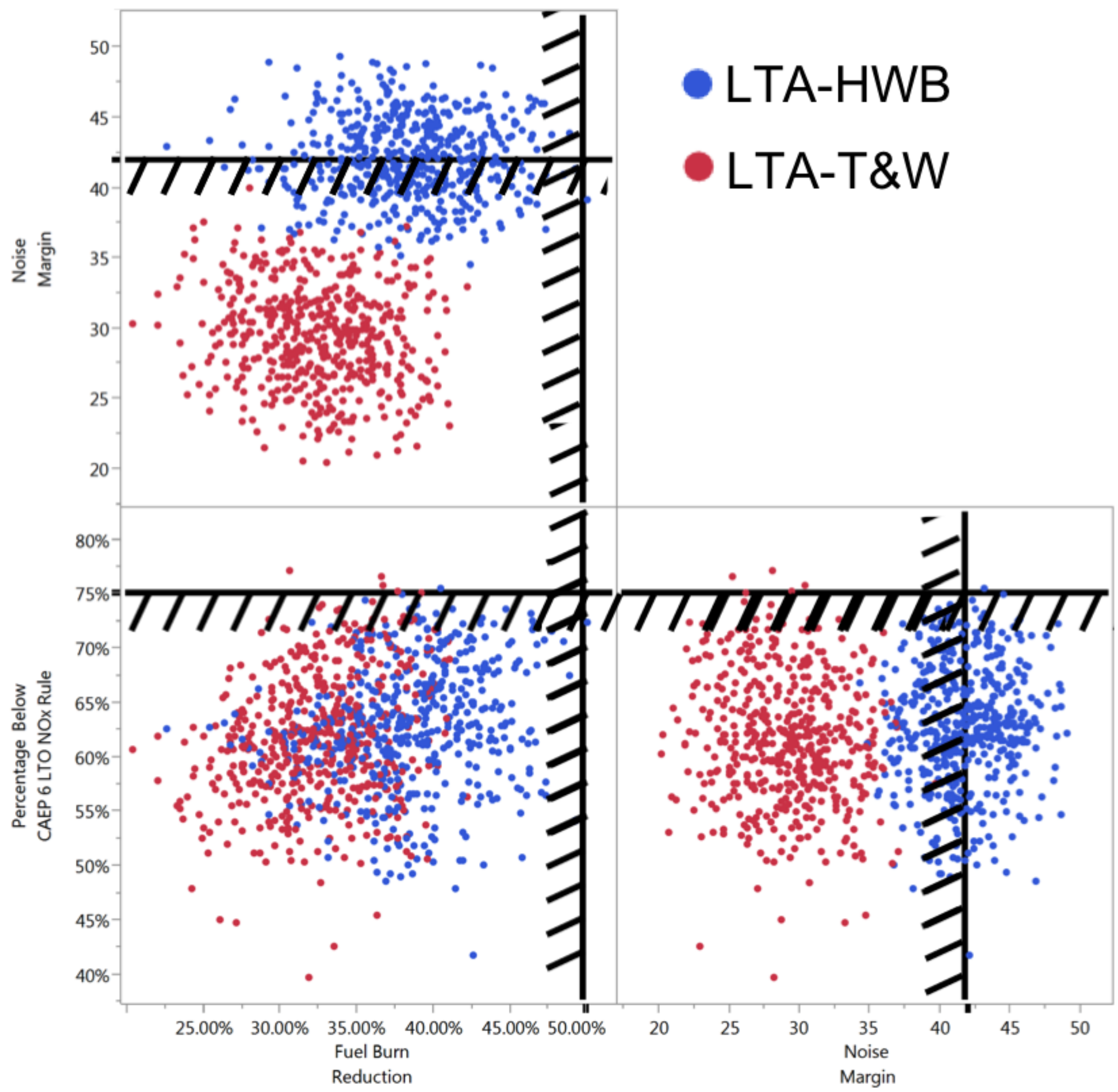

Figure 40: Performance comparison of the LTA and HWB vehicles with respect to fuel burn reduction, noise margin, and NOx emissions.

performance representation, because the assumption of a deterministic baseline may not be realistic. For example, the HWB concept is in reality less mature than the tube and wing concept and not currently operational in the commercial aviation setting. Therefore, it would incur some design uncertainty on top of the technology impact uncertainty which would correspond to a larger range of results for the probabilistic performance assessment for the HWB architecture. Figure 41 provides a new uncertainty depiction for the HWB architecture where other types of uncertainty, such as design uncertainty, was simulated to show how it could impact the results. As the figure shows, the additional uncertainty could cause the potential performance to improve. Likewise, however, it could also cause it to significantly degrade. This is readily observed because the noise margin gap between the two vehicle architectures is now closed and the fuel burn performance of the HWB is not guaranteed to outrank the potential fuel burn performance of the LTA.

It was previously acknowledged that an architecture is selected based solely upon performance. Other factors must be considered, including flight readiness of the system, airport infrastructure adaptability, defined certification processes, and safety assessments. For example, the HWB architecture is much different from the tube and wing concept that is currently utilized for commercial aviation. Therefore, current certification processes and safety statistics are no longer applicable, which could cause uneasiness in investors and future customers. Furthermore, commercial aviation infrastructure is compatible with a tube and wing configuration and may need altered to be compatible with the HWB concept.

Based on this discussion, it would be important for decision makers to consider many other risk aspects outside of performance risk. However, the objective of this step in the methodology is to provide the means for a performance assessment based upon probabilistic assessments. The probabilistic results in Figure 40 and Figure 41 demonstrate that the HWB architecture provides the best potential for the goals to

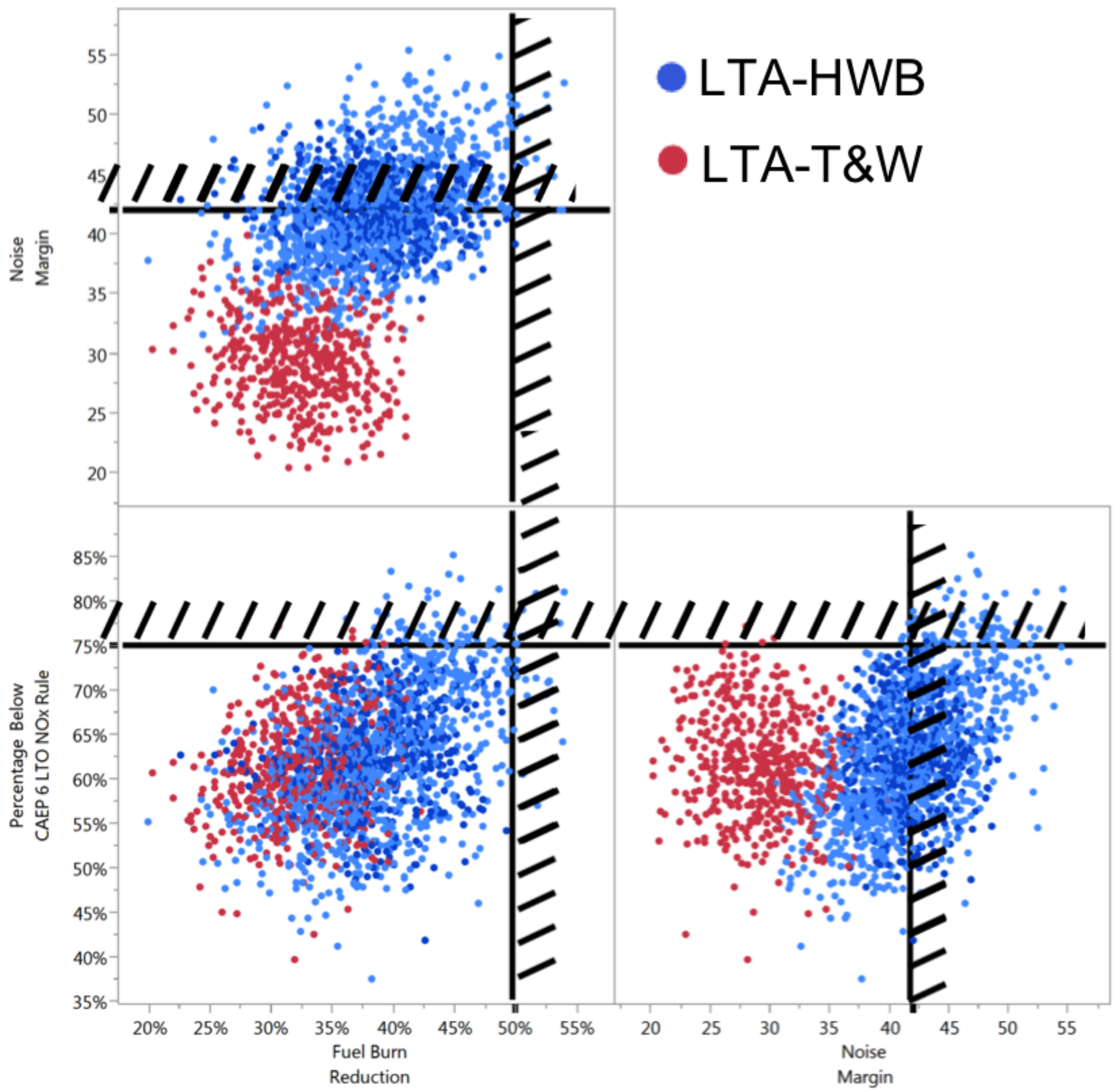

Figure 41: Probabilistic performance comparison of the three aircraft models with the inclusion of simulated design uncertainty for the HWB architecture.

be met. Therefore, if only potential performance is considered decision makers would select the HWB aircraft.

5.1.2 Identification of Key Impacts

After a vehicle architecture is selected, the impacts or k-factors driving the performance objectives are identified to guide technology identification. Furthermore, the amount of an impact and groupings of impacts that enable the goals to be met is desired. The process for acheiving this outlined through Hypothesis 1.2 and Hypothesis 1.3 is shown in Figure 42. This process involves the use of surrogate models to enable sensitivity analyses and a forecasting assessment. The following sub-sections provide a demonstration and test of this process.

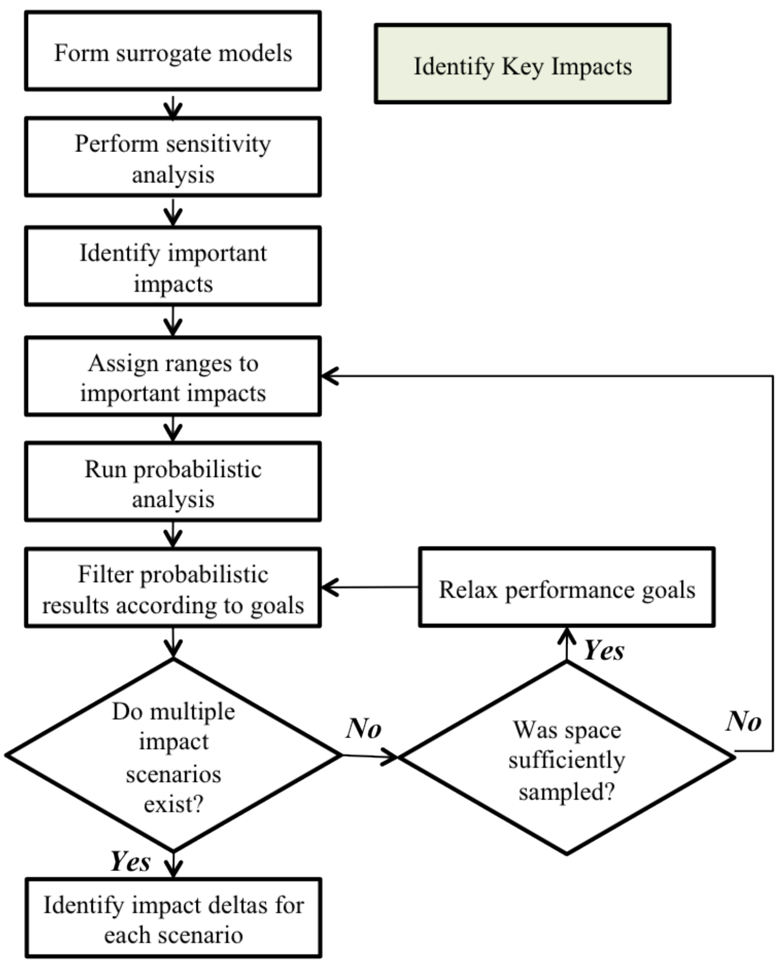

Figure 42: Process flowchart for identifying key performance impacts.

5.1.2.1 Identification of Impacts Driving Performance Objectives

For this part of the experiment set the LTA vehicle was utilized. Sensitivity analysis was used to assess how the LTA vehicle performance is affected by each of the 56 lower-level metrics identified for the probabilistic performance analysis. As described in Chapter Two, there exists several types of sensitivity analyses. For this research both local and global sensitivity approaches were tested. However, the use of either type of sensitivity analysis requires a reduction in computational expense of the EDS environment so surrogate models were formed.

Many different types of surrogate models exist in the literature, and Artificial Neural Networks (ANN) were selected for this research due to their ability to capture the complexity and non-linearity of the EDS environment. The ANNs were created by forming a 15,000 case DOE that captures the ranges of the k-factors identified previously for the architecture performance assessment. The ANNs were fit by utilizing a large sub-set of the 15,000 cases and the goodness of fit for each ANN was tested using the remaining cases. The performance of each ANN is guaranteed to be within $\pm 1\%$ of the actual EDS output.

Important metrics identified for each of the three objective metrics may not result in the same set due to the fundamental physics. An assessment of the correlation among the three metrics provides insight into the trade-offs that may be required in the future to achieve the goals. Figure 43 provides the results of the correlation analysis. The results show that fuel burn reduction and noise margin have a moderate negative correlation, fuel burn and NOx emissions have a low to moderate positive correlation, and noise margin and NOx emissions have a moderate negative correlation. A negative correlation implies that capabilities that aim to improve one metric may degrade another, while a positive correlation implies that capabilities improving one metric may also improve the other. The strength of the correlation determines the likelihood that the observed trend will be noticed. Therefore, it is expected that impacts driving the noise margin will show a moderate negative impact on both fuel burn and NOx emissions.

Correlations

	Fuel Burn Reduction	Noise Margin	Percentage Below CAEP 6 LTO NOx Rule
Fuel Burn Reduction	1.0000	-0.4077	0.2251
Noise Margin	-0.4077	1.0000	-0.3985
Percentage Below CAEP 6 LTO NOx Rule	0.2251	-0.3985	1.0000

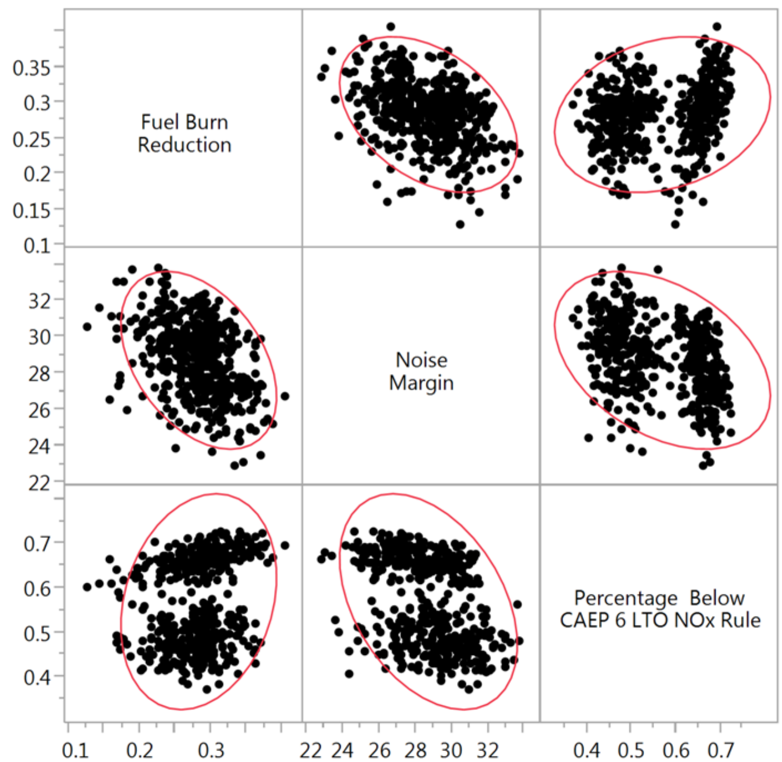

Figure 43: Analysis of correlation between fuel burn reduction, noise margin, and NOx emissions for LTA vehicle.

The information from the correlation assessment determined that it was important to perform sensitivity analyses on all three objective metrics. The first sensitivity analysis performed was a local approach. The type of local sensitivity analysis pursued was through the use of a prediction profiler. The prediction profiler displays the prediction traces for each factor, which are defined as the predicted response in which one factor is changed while the others are held at their current values[57]. Figure

44 provides a depiction of a generic prediction profiler and identification of its key parts. The vertical axis contains the responses of interest and the horizontal axis contains each of the factors being analyzed. The effect of the factors on each response can be determined by observing the magnitudes and directions of the slopes in the corresponding boxes. This type of assessment is only able to calculate first order effects, so the affect of interactions between variables with respect to the objectives is not quantified.

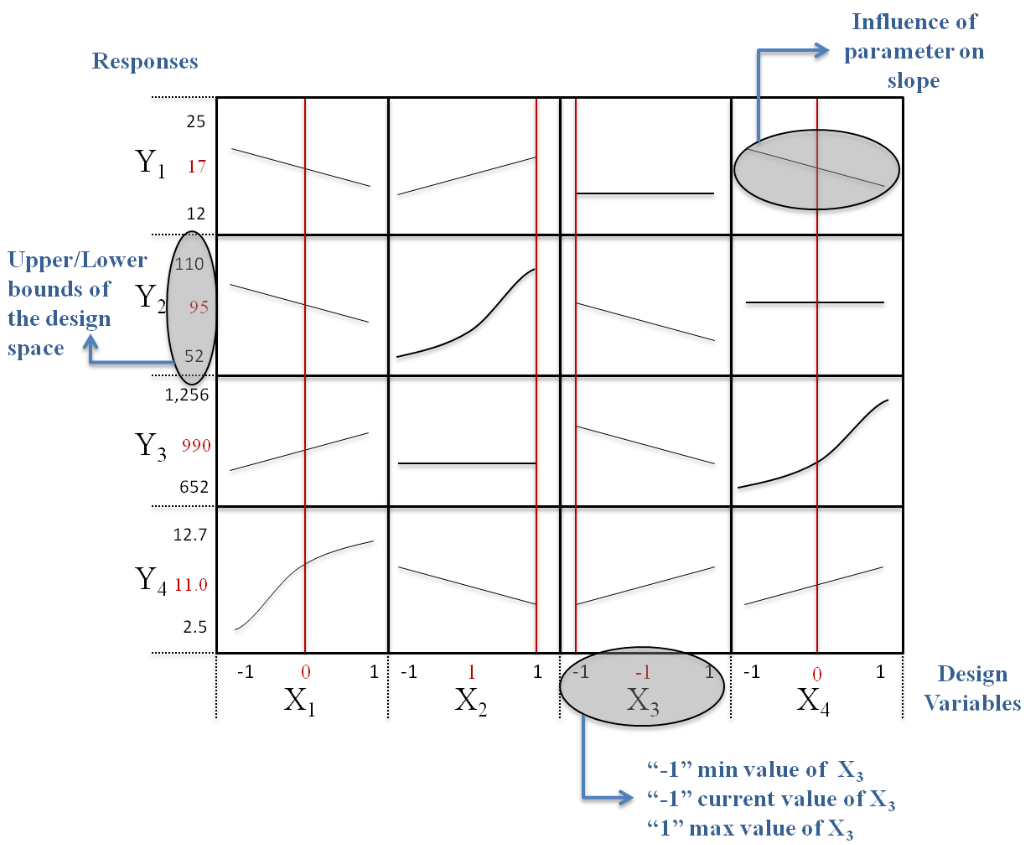

Figure 44: Depiction of interactive, parametric sensitivity analysis tool.

Figure 45, Figure 46, Figure 47, and Figure 48 display the results of the local sensitivity analysis. In addition to the three main objective responses, which are shown at the top of the vertical axis, several additional metrics were also analyzed. These metrics range among low level metrics, mid level metrics, and high level metrics of the aircraft system. While none of these metrics are direct inputs for the objective ANNs, they can be related. The additional metrics tracked are as follows: TOGW, operating empty weight (OEW), wing weight, fuselage weight, horizontal tail weight, vertical tail weight, bypass ratio (BPR), overall pressure ratio (OPR), and thrust specific fuel consumption (TSFC).

The prediction profiler results provide the identification of trends with respect to how the k-factors are driving the intermediate performance metrics as well as the objective metrics. It is identified in Figure 45 and Figure 46 that the weight factors, such as the fuselage weight factor and wing weight factors, have a noticeable impact on fuel burn reduction and the intermediate weight metrics like fuselage weight and OEW. Furthermore, in Figure 47 and Figure 48 it is noticeable that noise suppression factors, such as suppression factors on fan discharge noise and suppression factors on inlet noise, are driving the noise margin and engine pressure ratios and efficiencies are impacting the NOx emissions.

Identification of trends enables a confirmation that the environment is capturing the proper physics, which is beneficial for model validation purposes. However, it does not enable a straightforward quantitative ranking of the k-factors with respect to the performance objectives. Therefore, the a global SA technique was tested. The global approach considered was an analysis of variance (ANOVA) technique. ANOVA was performed for each of the goal metrics individually. The results of this analysis are displayed in Figure 49 with the fuel burn reduction results shown first, the noise margin results shown in the middle, and the NOx emissions reduction shown last. The results are displayed by using tornado plots. In each tornado plot, the factors with the greatest impact are the ones at the top of the graph with the longest bar chart. The direction of the bar for each factor provides the direction of influence of the factor. For example, the factor with the largest impact on fuel burn reduction is FRFU, which is the fuselage weight factor. The bar for FRFU is leftwards facing, which implies that

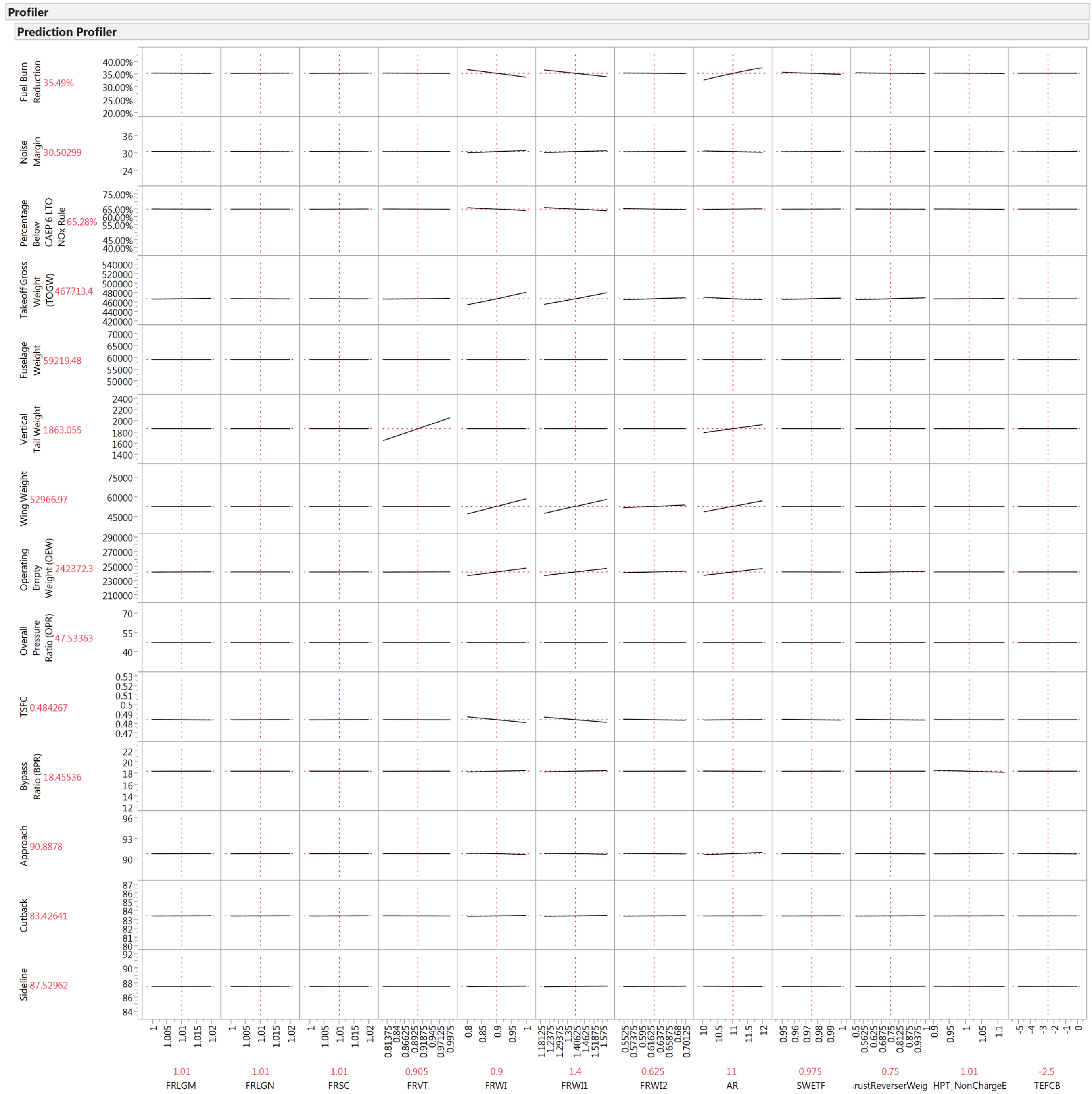

Figure 45: Prediction profiler sensitivity study for aircraft sizing and flowpath variables, Part 1.

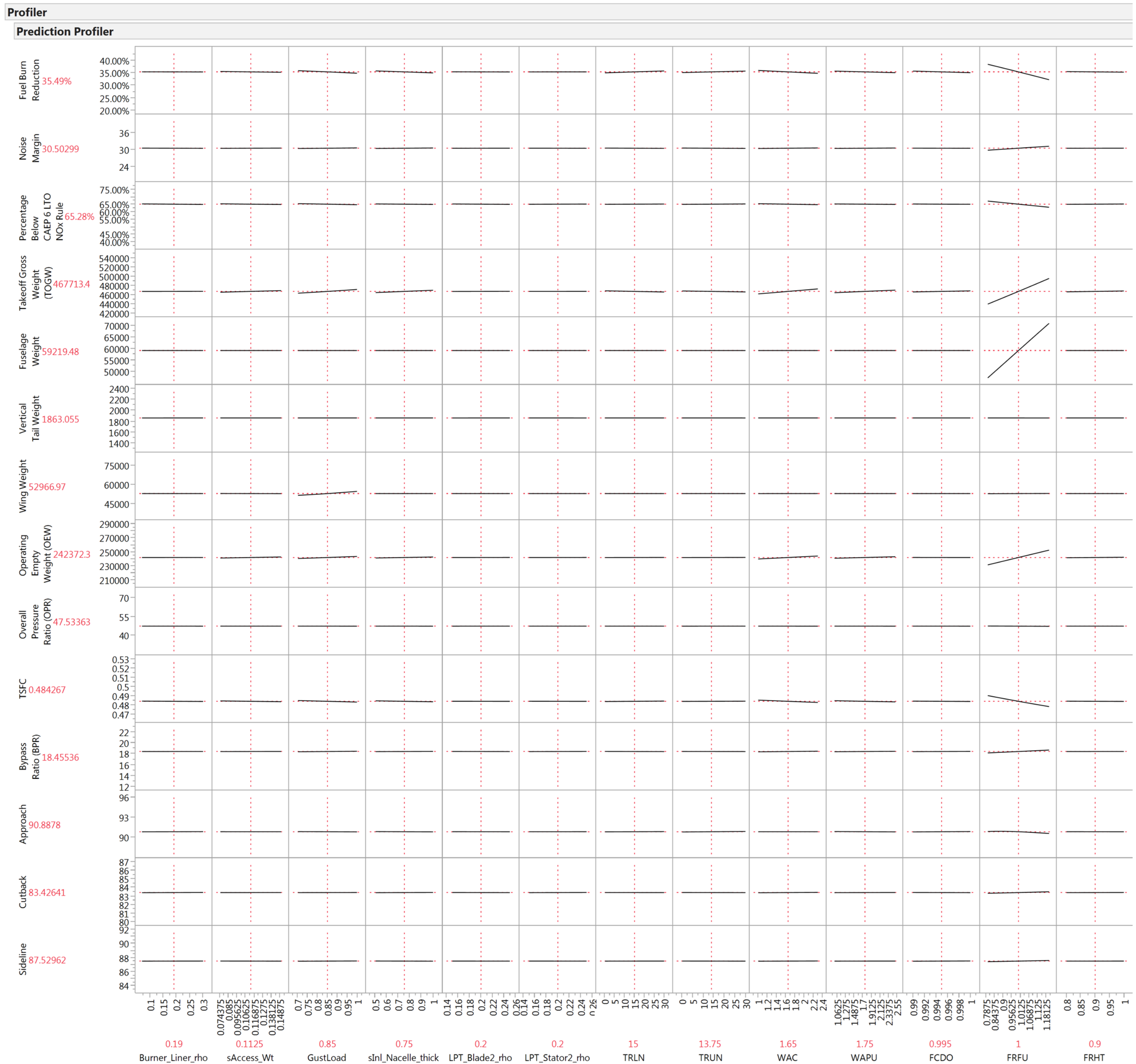

Figure 46: Prediction profiler sensitivity study for aircraft sizing and flowpath variables, Part 2.

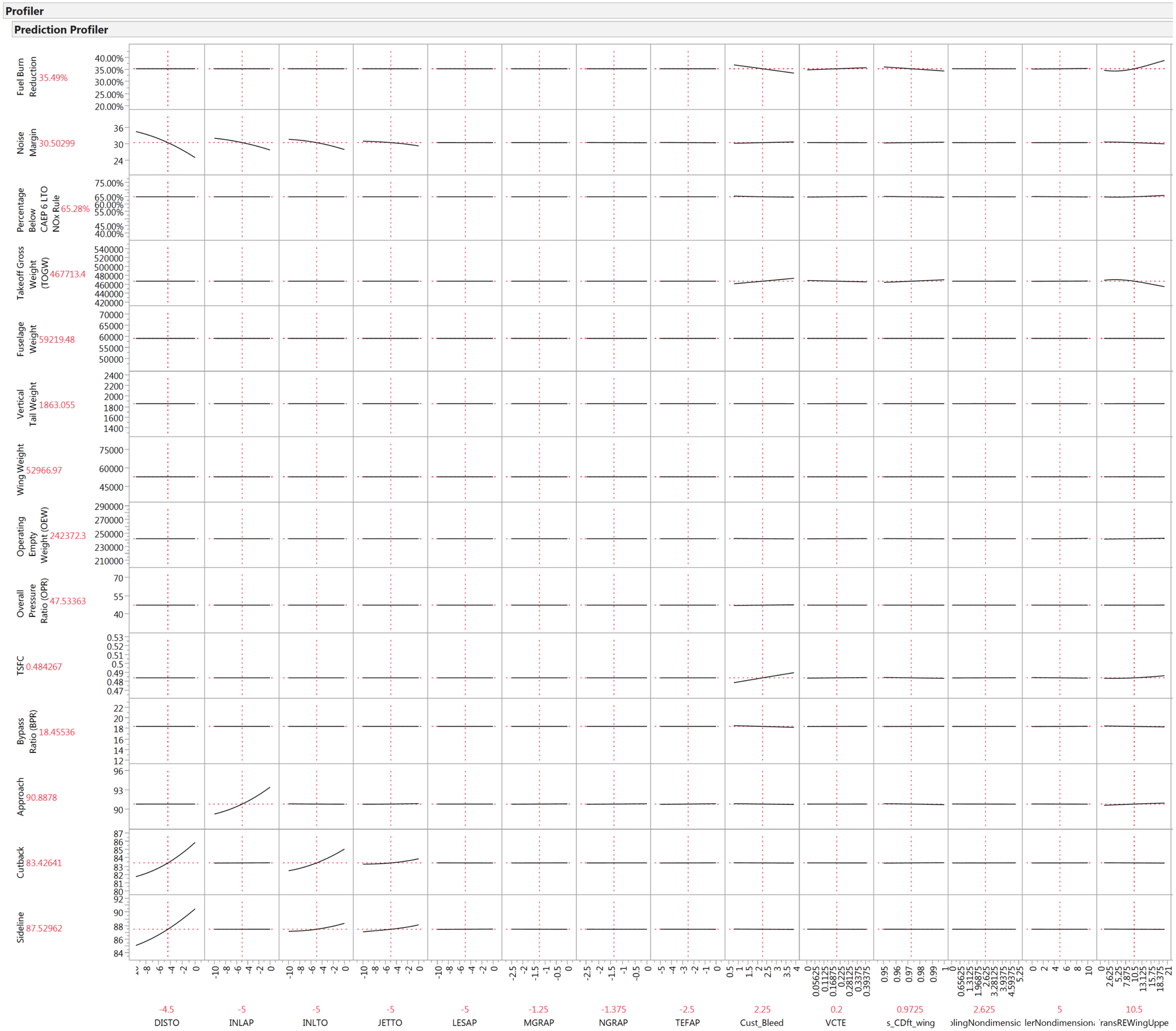

Figure 47: Prediction profiler sensitivity study for engine design variables and noise factors, Part 1.

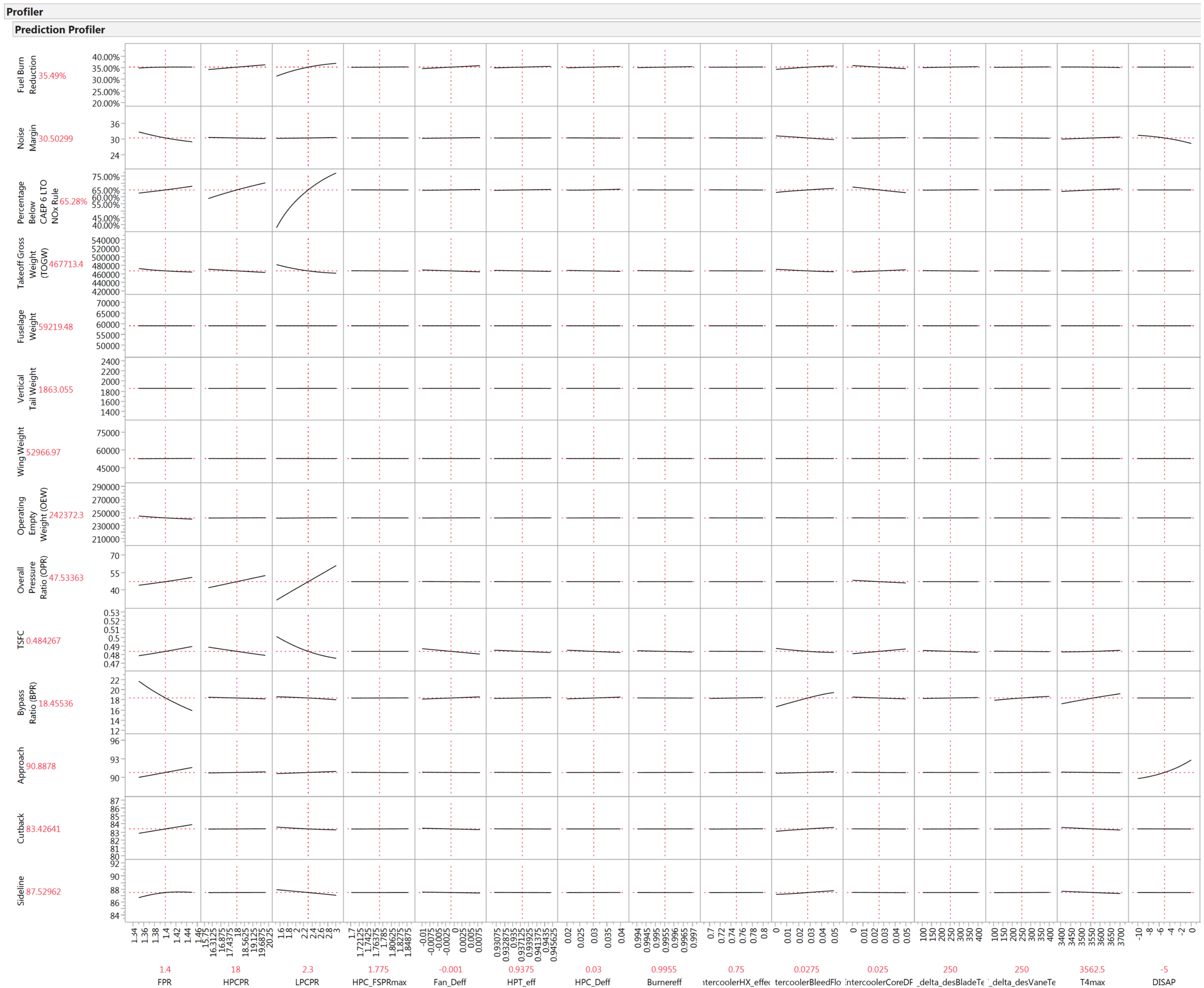

Figure 48: Prediction profiler sensitivity study for engine design variables and noise factors, Part 2.

the fuel burn reduction will increase as the value for FRFU decreases. In contrast, the factor with the largest impact on the NOx emissions is IntercoolerBleedFlow, and it is leftwards facing. This implies that the value for NOx emissions reduction will increase as the value for IntercoolerBleedFlow increases.

The ANOVA analysis has the ability to calculate the impact of higher order effects in addition to first order effects. After conducting the ANOVA analysis second and third order effects were calculated and it was discovered that few were relevant for each of the three objectives. Therefore, the rest of this analysis focuses solely on first order effects of the impact variables with respect to the three objectives. Furthermore, Figure 49 does not provide first order effects for the three responses. Instead, only factors that have been deemed important are displayed in the tornado plots. In this context, a factor was identified as important if it has a an individual p-value greater than or equal to 0.01.

The results produced from the ANOVA assessment enable the clear identification of factors that impact the three objective metrics the most. Therefore, no other sensitivity analysis approaches were considered because the objective had been met. Next, the amount of change required for a specific impact, or sets of impacts, is investigated through the identification of impact scenarios.

5.1.2.2 Identification of Impact Scenarios

The identification of impact scenarios provides insight into the combinations of impacts that development programs should pursue as well as the amount of capability improvement required. The identification of individual impacts that drive the performance is important, but attacking a single impact will not result in meeting aggressive performance objectives. When a large number of potential impacts exists, such as the 56 k-factors identified for the LTA vehicle, it can be difficult to identify all of the favorable combinations.

Screening for Fuel Burn Reduction

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
FRFU	-0.018733	-51.13	<.0001*
AR	0.016000	43.67	<.0001*
LPCPR	0.014359	39.19	<.0001*
TransREWingUpper	0.014634	39.94	<.0001*
FRWI	-0.009259	-25.27	<.0001*
LPT_Deff	0.008547	23.33	<.0001*
Cust_Bleed	-0.008262	-22.55	<.0001*
FRWI1	-0.008218	-22.43	<.0001*
HPCPR	0.006017	16.42	<.0001*
s_CDft_wing	-0.004406	-12.03	<.0001*
WAC	-0.004141	-11.30	<.0001*
Fan_Deff	0.003205	8.75	<.0001*
GustLoad	-0.003017	-8.23	<.0001*
VCTE	0.002608	7.12	<.0001*
FPR	0.002531	6.91	<.0001*
sInl_Nacelle_thick	-0.002297	-6.27	<.0001*
TRLN	0.002223	6.07	<.0001*
WAPU	-0.001943	-5.30	<.0001*
Burnereff	0.001917	5.23	<.0001*
TRUN	0.001715	4.68	<.0001*
HPC_Deff	0.001914	5.22	<.0001*
ThrustReverserWeight	-0.001391	-3.80	0.0001*
FCDO	-0.001259	-3.44	0.0003*
sAccess_Wt	-0.001299	-3.55	0.0002*
FRWI2	-0.001087	-2.97	0.0039*
FRHT	-0.000743	-2.03	0.0446*
IntercoolerHX_effect	0.000655	1.79	0.0762

Screening for Noise Margin

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
DISTO	-2.64990	-96.98	<.0001*
INLAP	-1.26430	-46.27	<.0001*
FPR	-1.11493	-40.81	<.0001*
INLTO	-0.95903	-35.10	<.0001*
DISAP	-0.83613	-30.60	<.0001*
JETTO	-0.54146	-19.82	<.0001*
FRFU	0.34207	12.52	<.0001*
LPCPR	0.19209	7.03	<.0001*
FRWI1	0.13898	5.09	<.0001*
FRWI	0.09514	3.48	0.0008*
HPCPR	-0.08741	-3.20	0.0015*
NGRAP	-0.07218	-2.64	0.0076*
Fan_Deff	0.06662	2.44	0.0152*

Screening for Percentage Below CAEP 6 LTO NOx Rule

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
IntercoolerBleedFlow	0.045112	52.25	<.0001*
LPCPR	0.021025	24.35	<.0001*
T4max	0.009661	11.19	<.0001*
FPR	-0.007164	-8.30	<.0001*
IntercoolerCoreDP	-0.006653	-7.71	<.0001*
HPC_Deff	0.005147	5.96	<.0001*
LPT_Deff	0.003141	3.64	0.0002*
IntercoolerHX_effect	0.002925	3.39	0.0011*
HPCPR	0.002972	3.44	0.0008*
IntercoolerNondimensionalWeight	-0.002382	-2.76	0.0076*
LPT_delta_desBladeTemp	0.001804	2.09	0.0399*
LPC_Deff	0.001622	1.88	0.0619

Figure 49: Analysis of variance screening test for fuel burn reduction, noise margin, and NOx emissions.

Identification of combinations of variables is not the only aspect of creating impact scenarios. The values for each of the individual impacts must also be identified. This dimension adds to the combinatorial aspect of the problem and rules out the possibility of creating a full factorial set of possible impact scenarios. Therefore, the design space created by the k-factor ranges should be thoroughly explored.

The ranges for the 56 k-factors defined previously were utilized to create the design space for impact scenario identification. Furthermore, the sampling of this space and resulting probabilistic performance assessments utilized for *Architecture Selection* are relevant for impact scenario identification. Therefore, the LTA results shown in Figure 40 represent potential impact scenarios and they can be filtered with respect to the defined goals. Recall, the original N+2 goals for the ERA program presented in Figure 35 are a 50% fuel burn reduction, 42dB noise margin, and 75% LTO NOx emissions reduction below the CAEP 6 rule. For the LTA vehicle, it is clear that the three goals cannot be simultaneously for any of the forecasted cases. At this point two options are available to pursue: identify new cases until viable options are discovered or relax the performance goals. It was felt that the design space was sufficiently sampled so the goals were relaxed.

Several new combinations of goals were considered and tested until a goal set that can be met simultaneously by multiple cases was identified. The goal set utilized for this portion of the research is a 35% fuel burn reduction, a 32dB noise margin, and a 65% NOx emissions reduction below the CAEP 6 rule. After filtering the cases for the LTA vehicle, eleven cases remained to be used as impact scenarios. Figure 50 shows the new goals overlaid on the LTA probabilistic performance results. It can be identified from Figure 50 that there are several other cases that meet at least one of the three goals, but only the points highlighted in red meet all three simultaneously. These points are the eleven identified impact scenarios. The performance attributes of the eleven impact scenarios are displayed in Table 12. There is no single impact scenario that dominates the performance for all three goals. Impact Scenario 10 provides the best fuel burn performance, Impact Scenario 2 provides the best NOx emissions performance, and Impact Scenario 6 provides the best noise margin.

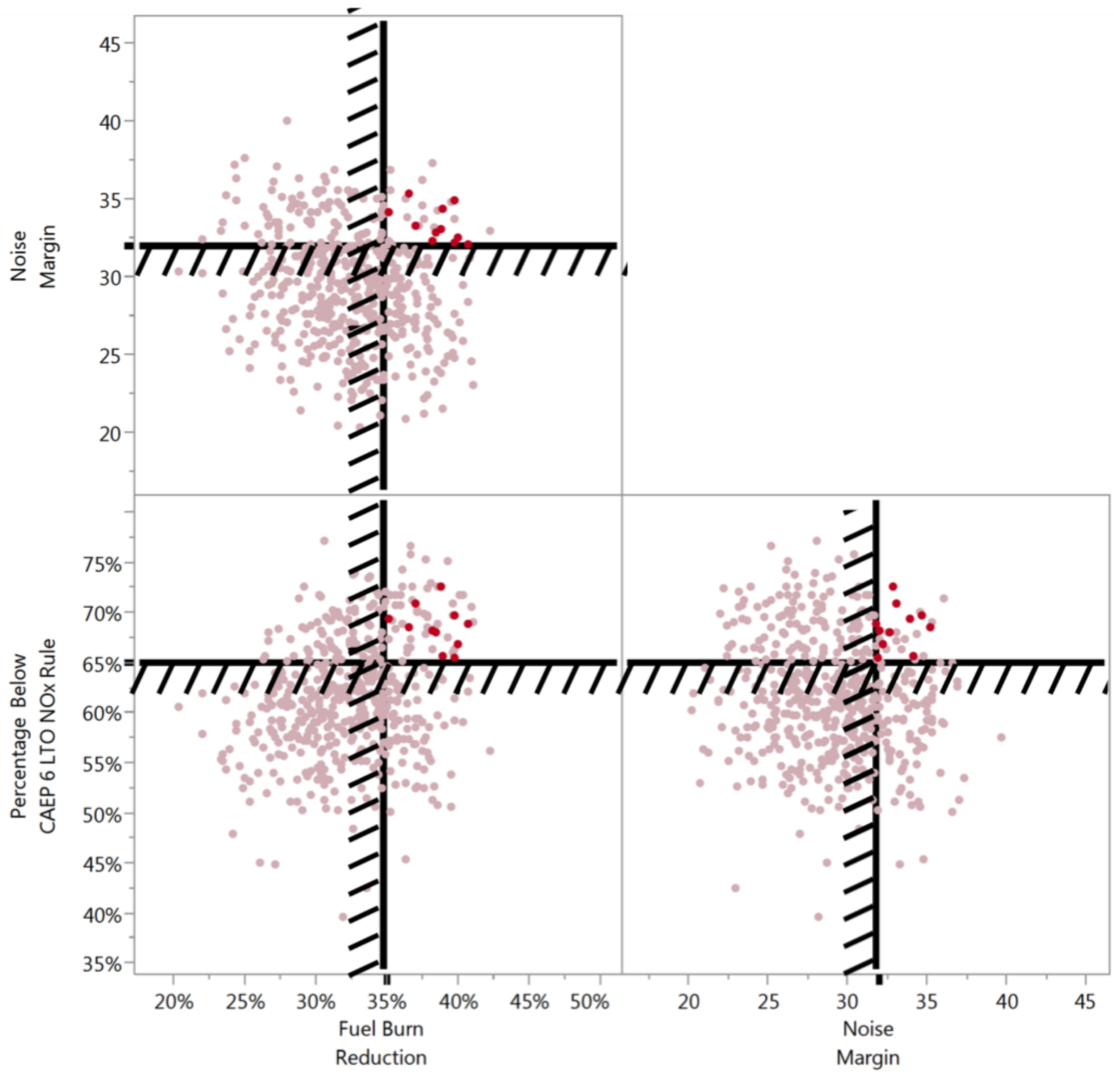

Figure 50: Identification of impact scenarios from LTA probabilistic performance results filtered with new goals.

Next, the individual impacts within each scenario were investigated. The required impacts are defined as deltas with respect to the vehicle baseline. The 2010 vehicle baseline was utilized, and the deltas were calculated by subtracting the values for the baseline variables from the variable values for each impact scenario. This enables the

Table 12: Performance of identified impact scenarios and the number of impacts affected.

Impact Scenario Number	Fuel Burn Reduction	Noise Margin	Reduction Below CAEP 6 LTO NOx Rule
Scenario 1	35.30%	34.10	69.31%
Scenario 2	38.97%	33.03	72.54%
Scenario 3	39.09%	34.30	65.68%
Scenario 4	39.94%	32.14	65.51%
Scenario 5	39.99%	34.90	69.73%
Scenario 6	36.75%	35.35	68.54%
Scenario 7	38.69%	32.83	67.96%
Scenario 8	40.21%	32.44	66.77%
Scenario 9	38.38%	32.23	68.22%
Scenario 10	40.94%	32.02	68.82%
Scenario 11	37.20%	33.29	70.90%

identification of how many variables are affected, which variables are affected, and by how much they are altered. The impacts can be defined at either the component level or mid-level. Describing the impact scenarios at an intermediate level provides a clearer picture of the types of impacts required. Therefore, the intermediate metrics provided in Figure 45, Figure 46, Figure 47, and Figure 48 were utilized. The result of this assessment are shown through a parallel plot in Figure 51. Each line in the parallel plot represents one of the LTA data points from Figure 50 and provides a visual depiction of how the design space is covered. The black lines represent the identified impact scenarios and the red line represents the 2010 baseline. It is easy to identify when each of the impact scenarios require an increase or decrease of a specific mid-level metric above the 2010 baseline or when there are a variety of values for a single impact variable. It is clear from Figure 51 that all scenarios have a decrease in operating empty weight (OEW), an increase in overall pressure ratio (OPR), and a decrease in horizontal tail weight, wing weight, and TOGW. These results make sense based upon the sensitivity analyses previously conducted and the discussion of the physics behind the objective metrics provided in Chapter Four.

The characteristics of the eleven impact scenarios provided by Figure 51 and Table 12 demonstrate the similarities and differences of the eight identified impact scenarios. Each of these impact scenarios could be pursued by either trying to achieve the impact

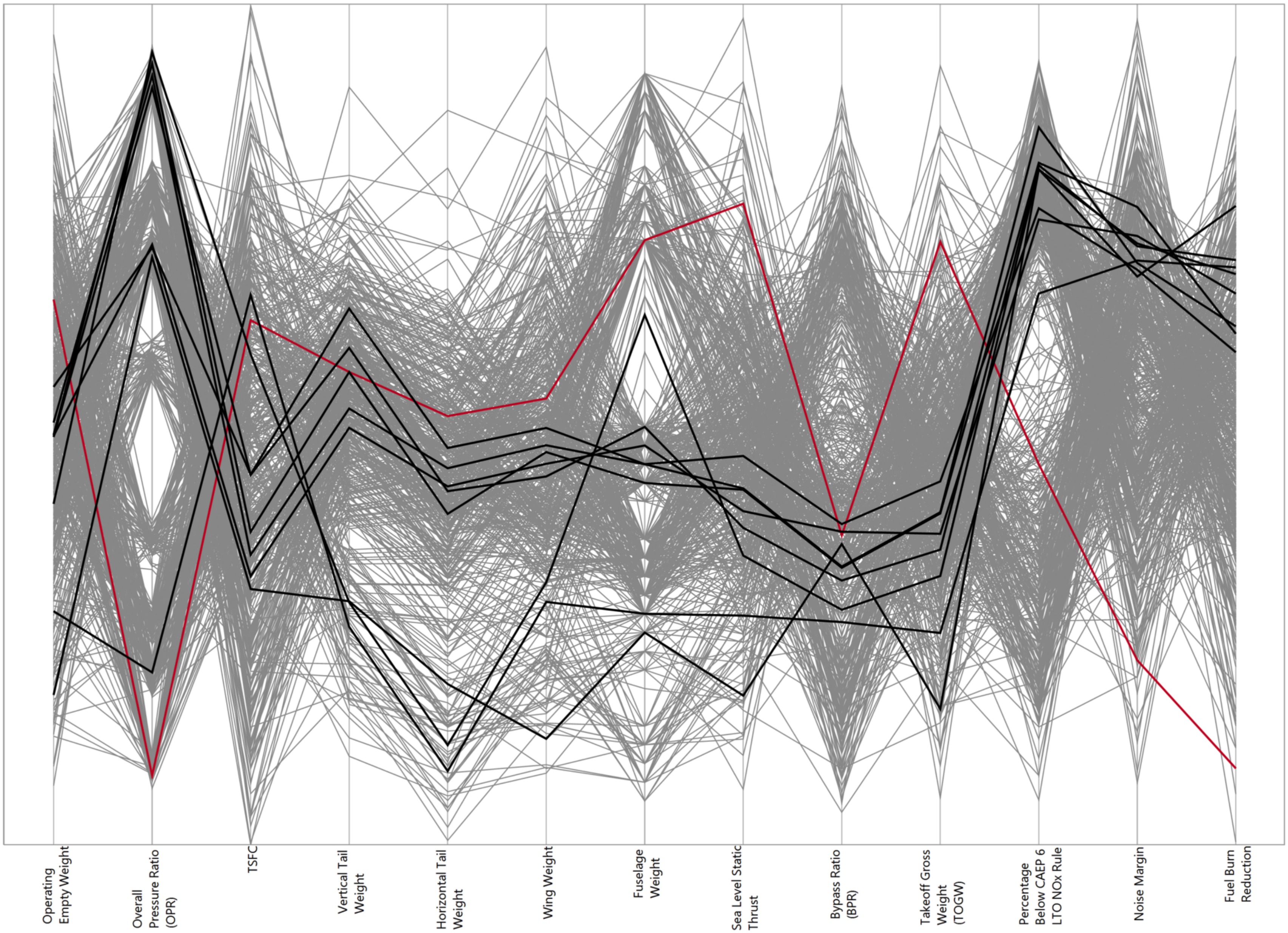

Figure 51: Parallel plot demonstrating the change in intermediate performance metrics for the eleven impact scenarios.

variable deltas or trying to achieve the mid-level metric deltas in order to achieve the system level performance. It is acknowledged, however, that meeting the mid-level metrics provided in Figure 51 will not necessarily guarantee the desired system level performance because there are other mid-level metrics that could also be affected.

5.1.3 Observations and Discussion

The research outlined in the previous subsections provided analysis that successfully aided the selection of a vehicle based upon forecasted performance assessments, the identification of key impacts that drive the objective metrics, and the identification of impact scenarios that enable the performance goals to be met. The processes followed in Experiment Set 1 map directly to the previously provided processes in Figure 39 and Figure 42.

The results of the experiment show that the architecture selection process demonstrated that a deterministic assessment of current state of the art vehicles can be leveraged to facilitate a probabilistic performance analysis. The method utilizes uncertainty quantification techniques and a modeling environment to provide depictions of the performance of potential future aircraft systems that enable comparisons among the vehicles. The resulting information enables architecture decisions to be made based upon the expected future performance of a given vehicle architecture. Therefore, this demonstrated process supports Hypothesis 1.1.

For the identification of key impacts, two types of sensitivity analyses were explored, a global approach and a local approach. The global approach enabled a quantitative comparison of the effects of the k-factors on the objective metrics whereas the local approach only provided an identification of trends. Furthermore, the local approach enabled a visual identification of trends among k-factors, lower and mid level metrics, and the objective metrics. Overall, the sensitivity analyses paired with the modeling environment were able to identify key impacts that drive the objective metrics and provide a quantitative comparison. Therefore, Hypothesis 1.2 is supported.

The second portion of Figure 42 focuses on identification of impact scenarios. A TIF-based process that samples the space to identify a set of impact scenarios was formulated and implemented. It resulted in the identification of several impact scenarios. It is acknowledged that the eleven impact scenarios identified are not the complete set. However, additional impact scenarios could be identified by further sampling the space or reducing the number of k-factors considered and re-implementing the process. Therefore, based upon these observations, Hypothesis 1.3 is supported.

5.2 Examination of Phase 2

The objective of Experiment Set 2 is to test Hypotheses 2.1, 2.2, 2.3, and 2.4. Recall, the goal of Phase 2 of technology development is to formulate relevant technology portfolios, analyze them, and then down-select a final technology portfolio to develop. It was previously acknowledged that the characteristics utilized to select an ideal technology portfolio can also be considered during portfolio formulation. Furthermore, the number of technologies included in a prospective portfolio is dependent on the resources available and other programmatic aspects. Since it is outside the scope of this research to investigate that aspect of a technology development program, the objective of *Formulate Technology Portfolios* in the QuantUM^3 methodology is to provide a means for technology prioritization based upon the performance impact of the technologies.

Different avenues for technology prioritization based upon performance were investigated, including the process outlined by Hypothesis 2.1. Each method was implemented and the results were compared. Next, a set of portfolios was analyzed to produce the relevant performance attributes and readiness attributes from Hypotheses 2.2 and 2.3. Performance and readiness risk characterizations were calculated and communicated through a set of visualizations to enable the identification of trends. A decision making process was then implemented to demonstrate how this information can be used to aid risk-informed decision making. Finally, a single technology portfolio was be analyzed to identify how supplemental technologies can be selected, which addresses Hypothesis 2.4.

Before any of the experimentation was performed, a set of technologies were obtained. The Aerospace Systems Design Lab (ASDL) at the Georgia Institute of Technology conducted a study for the NASA ERA project which resulted in the identification of a set of technologies relevant to the ERA performance goals. The technologies were identified through background research and by working with the NASA ERA systems analysis team and NASA technologists through various workshops. The ASDL research team synthesized all of the information on the technologies by documenting the assumptions and mapping the expected capabilities of each technology to relevant k-factor variables in the EDS environment.

The technologies identified in this study were documented in a final report presented to the NASA ERA project. This report was readily available and contains all relevant information regarding readiness and performance. Therefore, these technologies will be utilized for the technology super-set for this research.

There are a total of 88 technologies provided in the technology super-set and they are divided into six groups based upon the nature of their capabilities: engine fuel burn technologies, engine noise technologies, airframe aerodynamic technologies, airframe noise technologies, subsystem and structural technologies, and engine emissions technologies. The technologies are enumerated in Table 13 through Table 17 where each technology is described by both a technology identifier and a technology name. Additional information for each technology is provided in Appendix A. This information includes the EDS k-factor variables the technology impacts, the current TRL level of the technology, and the number of expected years until the technology reaches TRL 9.

Table 14: Engine Noise Technologies

Technology Identifier	Technology Name
T40	Fan Vertical Acoustic Splitter
T41	Blade Tone Control via Trailing Edge Blowing
T42	Noise Canceling Stator
T47	Fluidic Injection
T52	Short Nacelle Lip Liner
T53	Over the Rotor Acoustic Treatment
T54	Compound Rotor Sweep
T56	Soft Vane
T57	Stator Sweep and Lean
T59	Variable Geometry Chevrons

Table 13: Engine Fuel Burn Technologies

Technology Identifier	Technology Name	Technology Identifier	Technology Name
T36.5 + T38	Polymer Matrix Composites (PMC) - LPC Stator	T28.1	Advanced Turbine Superalloys - HPT Blades
T36.6 + T38	Polymer Matrix Composites (PMC) - LPC Blade	T28.2	Advanced Turbine Superalloys - HPT Vanes
T7	Solid Oxide Fuel Cell Auxiliary Power Unit	T28.3	Advanced Turbine Superalloys - LPT Blade
T77	Variable Area Nozzle	T28.4	Advanced Turbine Superalloys - LPT Vane
T20	Active Compressor Clearance Control	T29.1 + T31	CMC HPT Vane + Hi Temp Erosion Coating
T21	Active Compressor Flow Control	T29.2	CMC Exhaust Core Nozzle
T22.1	Compressor Intercooler	T29.3 + T31	CMC LPT Vane + Hi Temp Erosion Coating
T22.2	Cooled Cooling - Turbine	T33.1	Highly Loaded HP Turbine
T23	Active Turbine Clearance Control	T67	Advanced Engine Components
T24.B	Active Turbine Flow Control - GTF	T33.2	Highly Loaded LP Turbine
T25	Active Film Cooling	T93.2	Ti-Al - LPT Foreward Blades
T26.1	Advanced Powder Metallurgy Disk - HPC Last Stage Disc	T32.B	Highly Loaded Compressor
T27.1B	N+2 Advanced TBC Coatings - HPT Blade	T27.1C	ITD Advanced TBC Coatings - HPT Blade
T27.2B	N+2 Advanced TBC Coatings - HPT Vane	T27.2C	ITD Advanced TBC Coatings - HPT Vane
T27.3B	N+2 Advanced TBC Coatings - LPT Blade	T27.3C	ITD Advanced TBC Coatings - LPT Blade
T27.4B	N+2 Advanced TBC Coatings - LPT Vane	T27.4C	ITD Advanced TBC Coatings - LPT Vane

Table 15: Airframe Aerodynamics Technologies

Technology Identifier	Technology Name
T10.1	HLFC Suction - Wing
T10.2	HLFC Suction - Tails
T11.1	Natural Laminar Flow - Wing
T11.2	Natural Laminar Flow - Tails
T11.3	Natural Laminar Flow - Nacelle
T12.1	Riblets - Fuselage
T12.2	Riblets - Wing
T66	AFC Tail
T68	Advanced Aero Wing
T69.1	DRE for HLFC - Wing
T69.2	DRE for HLFC - Tail
T72	Low Interference Nacelle
T74	Thrust Reversers - Nacelles
T94	Adaptive Compliant Trailing Edge

Table 16: Airframe Noise Technologies

Technology Identifier	Technology Name
T14	Continuous Moldline Link for Flaps
T15	Flap Fences / Flaplets
T16.1	Landing Gear Integration - Main
T16.2	Landing Gear Integration - Nose
T17	Flap Edge Treatment
T18	Slat Inner Surface Acoustic Liner
T19	Slat-Cove Filler
T76	Active Pylons Shaping/Blowing

Table 17: Engine Emissions Technologies

Technology Identifier	Technology Name
T62 + T61	LDI + Active Combustion Control
T63	Lightweight CMC Liners
T64 + T61	LPP Combustor w/ TAPS + Active Combustion Control

Table 18: Structure and Subststem Technologies

Technology Identifier	Technology Name
T3.1	Damage Arresting stitched composites- Fuselage
T3.2	Damage Arresting stitched composites- Wing
T6	Electro Mechanical Flight Control Actuators
T78.1	Primary Structure Joining Methodologies - Wing
T78.2	Primary Structure Joining Methodologies - Fuselage
T79.1	Damage Tolerant Laminates - Wing
T79.2	Damage Tolerant Laminates - Fuselage
T79.3	Damage Tolerant Laminates - Tail
T80.1	Advanced Sandwich Composites - Wing
T80.2	Advanced Sandwich Composites - Fuselage
T80.3	Advanced Sandwich Composites - Tail
T81.1	Post-buckled Structure - Wing
T81.2	Post-buckled Structure - Fuselage
T82.1	Out-of-Autoclave Composite Fabrication - Wing
T82.2	Out-of-Autoclave Composite Fabrication - Fuselage
T82.3	Out-of-Autoclave Composite Fabrication - Tail
T83.1	Unitized Metallic Structures - Wing
T83.2	Unitized Metallic Structures - Fuselage
T83.3	Unitized Metallic Structures - Tail
T84.1	Tow Steered Composite Structure - Wing
T84.2	Tow Steered Composite Structure - Fuselage

5.2.1 Technology Portfolio Formulation

It has been established that technology portfolios should be formulated in an intelligent manner to ensure the resulting portfolios provide the desired characteristics. Furthermore, it was acknowledged in Chapter Three that when a small set of technologies exists to select from, it may be possible to formulate and analyze all potential technology portfolios. Relevant, or attractive, portfolios could then be identified through filtering based upon readiness and performance attributes of the full set of portfolios. However, as the number of candidate technologies increases, the viability of this approach diminishes. For example, there is an approximate total of $6.19e26$ possible portfolio for the 88 technologies in the provided technology super-set utilized for this research. This number is unmanageable due to both data storage limitations and analysis time. Assuming it takes only one second to analyze each technology portfolio, it would take approximately $1.97e19$ years to complete the analysis. Therefore, there is a need for technology prioritization.

As mentioned, several different approaches for technology prioritization for portfolio formulation based upon performance were investigated. The final process for *Formulate Technology Portfolios* is provided in Figure 52. Hypothesis 2.1 proposed a method to prioritize technologies based upon how they map to important lower level impacts from the identified impact scenarios. The results of the first part of Experiment Set 2 demonstrate how this may not be a sufficient process and the full process shown in Figure 52 is required. Discussion will be provided in the following sub-sections on how this resultant process was formulated.

5.2.1.1 Portfolio Formulation based on Impact Scenarios

The technology prioritization process proposed in Hypothesis 2.1 involves formulating technology scenarios with respect to how technologies map to impacts at the

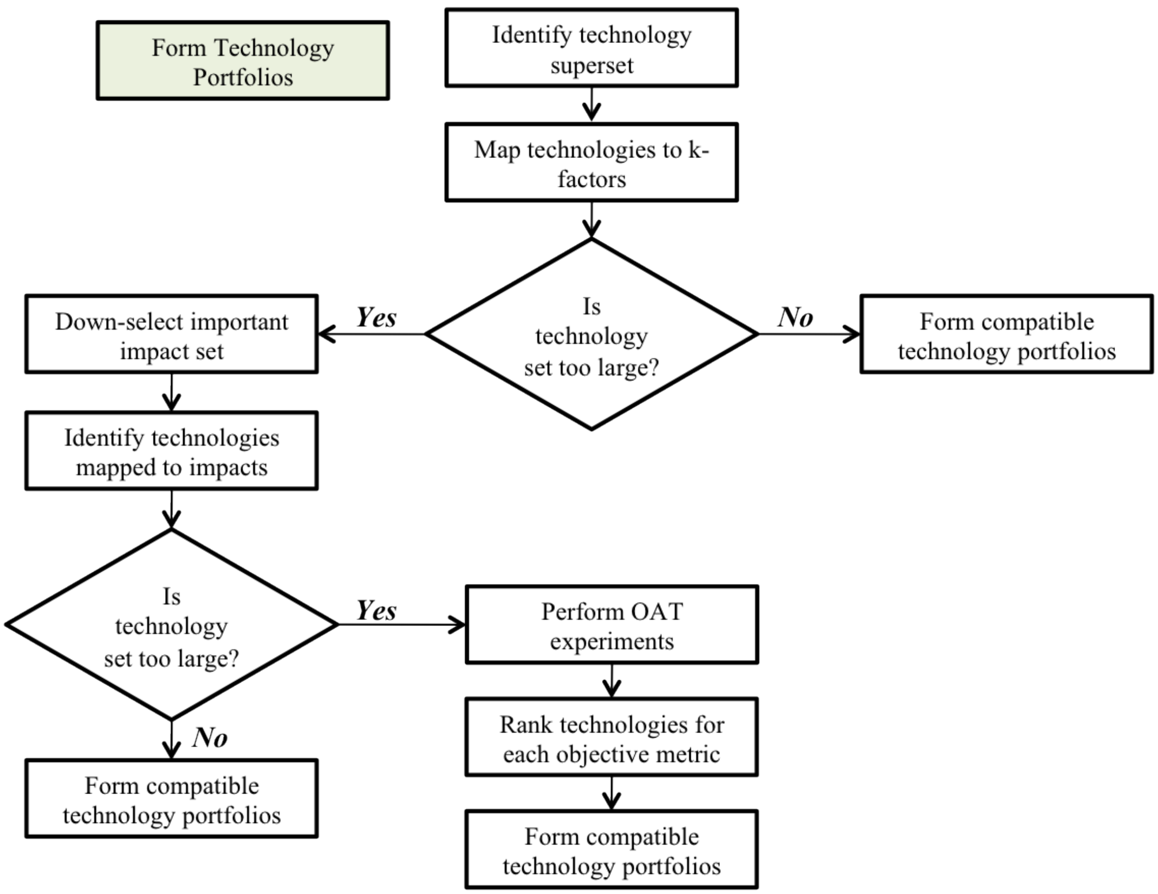

Figure 52: Process flowchart for formulating technology portfolios.

component or subsystem level. When utilizing the technology k-factor modeling approach, the effects of each technology are already mapped to impacts at this level. Therefore, part of the information required for this approach is readily available.

Two avenues were considered for this formulation. First, it is acknowledged that technology portfolios can be created strictly based upon the results of the sensitivity analyses. In this approach technologies that map to the top identified impact variables for each objective metric are considered for technology portfolios. Once all of the relevant technologies have been identified, different combinations can be formed to represent potential technology portfolios. The second avenue utilizes the previously identified impact scenarios. In this approach technologies that map to the variables affected in a given impact scenario are considered for inclusion in technology portfolios.

Some observations on the two outlined approaches were made preemptively before implementation was attempted. First, it was noted that prioritizing technologies based upon how they map to favorable impacts does not take into consideration the detrimental impacts a technology could impose on the system. What this implies is that a technology that maps to key impacts may not necessarily provide the expected beneficial performance. Next, it was acknowledged that utilizing the impact scenarios could result in having to consider and capture too many k-factors in a single technology portfolio. Note that the impact scenarios contain at least 39 affected k-factors. While 39 is a reduction from the original 56 variables, it still may result in a large subset of prioritized technologies because each k-factor may identify more than one relevant technology. Therefore, directly using the impact scenarios for technology prioritization will not provide enough of a prioritization.

Next, utilization of the results of a quantitative sensitivity analysis that provides the effects of the impact variables, or k-factors, on the system level objectives was investigated. It is acknowledged that the results of the ANOVA assessment provide the required information, so it can be directly utilized. Figure 49 provided the results of the ANOVA analysis and a list of the important k-factors for each objective metric. This information was utilized to identify technologies from the provided technology superset. The mapping of the technologies to the impacts is shown in Table 20, Table 19, and Table 21.

Table 19: Technologies identified for noise margin impacts

Variable Identifier	Technologies
DISTO	T56, T40, T49, T42, T57, T41
INLAP	T41, T52, T54, T42, T53, T57
FPR	None
INLTO	T42, T49, T53, T41, T52, T54, T57
JETTO	T47
FRFU	T3.1, T78.2, T79.2, T80.2, T81.2, T82.2, T83.2, T84.2
LPCPR	T22.1, T26.1
FRWI1	T80.1, T83.1, T84.1
HPCPR	T32.B
NGRAP	T16.2
Fan_ Deff	None

Table 20: Technologies identified for fuel burn reduction impacts

Variable Identifier	Technologies
FRFU	T3.1, T78.2, T79.2, T80.2, T81.2, T82.2, T83.2, T84.2
AR	T68
LPCPR	T22.1, T26.1
TransREWingUpper	T10.1, T11.1, T69.1
FRWI	T3.2, T78.1, T79.1, T81.1, T82.1
LPT_ Deff	T23, T67, T33.2
Cust_ Bleed	None
FRWI1	T80.1, T83.1, T84.1
HPCPR	T32.B
s_ CDft_ wing	None
WAC	T73, T10.1, T10.2
Fan_ Deff	None
GustLoad	T68, T94
VCTE	T8, T94
FPR	None
sInl_ Nacelle_ thick	T72
TRLN	None
WAPU	T7
Burnereff	T62+T61
TRUN	T11.3
HPC_ Deff	T20, T67
ThrustReverserWeight	None
FCDO	T72
sAccess_ Wt	T62+T61, T64+T61, T20,T23, T25, T21
FRWI2	T80.1, T83.1, T84.1
FRHT	T79.3, T80.3, T82.3, T83.3
IntercoolerHX_ effect	T22.1

Table 21: Technologies identified for NOx emissions impacts

Variable Identifier	Technologies
IntercoolerBleedFlow	T22.1
LPCPR	T22.1, T26.1
T4max	None
FPR	None
IntercoolerCoreDP	T22.1
HPC_ Deff	T20, T67, T32.B
LPT_ Deff	T33.2, T33.1, T67
IntercoolerHX_ effect	T22.1
HPCPR	T32.B
IntercoolerNondimensionalWeight	T22.1
LPT_ delta_ desBladeTemp	T27.3B, T28.3B, T27.3C
LPC_ Deff	T67

The mapping of technologies to the key impacts results in the prioritization of 69 technologies. While this is a reduction from the original 88 technologies, it still leaves a large number of potential technology portfolios. Based on this information, further prioritization of technologies should be pursued. Therefore, two additional approaches that could provide the means for technology prioritization were investigated.

5.2.1.2 Portfolio Formulation based on Multi-Objective Genetic Algorithm

As mentioned, the identification of all relevant technology portfolios through a manual approach may become cumbersome if a large number of technologies exists. Furthermore, when the objective is to identify portfolios that offer the absolute best potential performance, it may be difficult to identify the optimal set even if the manual approach is thorough and systematic. An automatic, structured approach was discovered in the literature that tackles this problem through the use of a multi-objective genetic algorithm.

The method developed by Jimenez et al.[43, 44] was motivated by the desire to identify the most favorable combinations of technologies relative to a set of performance goals. The method was formulated by defining the technology portfolio selection problem as follows. A set, τ, of technologies, T_i, is:

$$\tau = \{T_1, T_2 \ldots, T_n\} \tag{34}$$

An single combination of technologies is then defined by the vector t,

$$t = [t_1, t_2 \ldots, t_n] \tag{35}$$

Where t_i is equal to 1 if T_i is included and equal to 0 otherwise. Technology combinations must include compatible technologies, so a compatibility operator, χ, is defined on a pair-wise basis as

$$\chi(T_i, T_j) = \chi_{ij} = \begin{cases} 1, & if\ T_i\ is\ compatible\ with\ T_j \\ 0, & if\ T_i\ is\ not\ compatible\ with\ T_j \end{cases} \tag{36}$$

When there exists no technology incompatibilities, which corresponds to all $\chi_{ij} = 1$, there exists 2^n possible technology combinations. This set is referred to as the domain of alternative space, A. Therefore, the set of compatible technology combinations can be defined as $A^\chi \subseteq A$.

For this formulation, the objective functions are evaluated for the technology combinations, which is expressed as

$$f_m(t), m = 1, 2, \ldots, M \tag{37}$$

This method utilizes the technology k-factor modeling approach. Therefore, there is a need to map the objective function from the technology space to the k-space such that

$$\vec{f} : t \to k \tag{38}$$

Therefore, the objective function f with argument t is expressed as:

$$f(t) = f^k\left(\vec{f}(t)\right) \tag{39}$$

Compatibility of technology combinations is addressed by utilizing an arbitrarily large penalty factor into the objective function for incompatible technologies to ensure they would never be selected. The compatibility of a combination t^l is calculated by estimating the parameter ϕ^l

$$\phi^l = \Pi\chi_{ij} \qquad \forall i, j : t_i^l = 1 \wedge t_j^l = 1 \tag{40}$$

The penalty factor can be simplified because the inclusion of at least one incompatibility will always cause the product to be zero. It can therefore be defined as

$$\pi^l = \begin{cases} \wedge & if \quad \phi^l = 0 \\ 1 & if \quad \phi^l = 1 \end{cases} \tag{41}$$

In this context, $\wedge$ is a constant that yields a large penalty to the objective function. The penalty function is incorporated into the objective function as

$$\bar{f}(t) = \pi^l f^k\left(\vec{f}(t)\right) \tag{42}$$

After addressing compatibility and the penalty function, the optimization problem is formulated as

$$\begin{aligned} Min/Max\ Subject\ to: \qquad & f(t), \\ & \phi(X,t) > 0 \\ & t \in A \end{aligned} \tag{43}$$

Furthermore, if the pseudo-objective function is to be explicitly stated, the optimization problem is formulated as

$$\begin{aligned} Min/Max\ Subject\ to: \qquad & \tilde{f}(t), \\ & t \in A \end{aligned} \tag{44}$$

The selection of the appropriate algorithm to solve the optimization problem is required. In the context of the problem Jimenez et al. tackled, they desired a multi-objective optimization scheme because multiple performance objectives were desired to be met. For a set of performance objectives,

$$\tilde{f}_m(t); \quad m = 1, 2, \ldots, M \tag{45}$$

a technology combination t^i strongly dominates t^j if t^i is better than t^j in all M performance objectives, or

$$t^i \prec t^j \leftrightarrow \tilde{f}_m\left(t^i\right) \prec \tilde{f}_m\left(t^j\right) \forall m \tag{46}$$

In contrast, t^i weakly dominates t^j if t^i is no worse than t^j in all M performance objectives and t^i is better than t^j in at least one objective, or

$$t^i \preccurlyeq t^j \leftrightarrow \tilde{f}_m\left(t^i\right) \preccurlyeq \tilde{f}_m\left(t^j\right) \forall i \wedge \exists l : \tilde{f}_l\left(t^i\right) \prec \tilde{f}_l\left(t^j\right) \tag{47}$$

The set of technology combinations that are not dominated by any other technology combination is the non-dominated set. When A is the total set of technology combinations and B is a subset of solutions from A, B' is a non-dominated set of solutions such that

$$B' \subset B \subset A \tag{48}$$

The overall purpose of the optimization routine is to identify the non-dominated set A' from A. In circumstances where A' cannot be identified, it is approximated through B'. The selection of A' can be done through the use of any multi-attribute selection technique. One common technique is a weighted sum of scaled values, shown as

$$F\left(t^i\right) = \sum_{m=1}^{M} w_m \frac{f_m\left(t^i\right)}{f_m\left(t\right)^*} \tag{49}$$

where the asterisk denotes the normalizing function value.

Jimenez et al. combined this problem formulation with an existing genetic algorithm routine to create their multi-objective genetic algorithm process for technology portfolio selection, which will be referred to as MOGA. The MOGA method is implemented through a set of MATLAB routines where the required inputs are the technologies, their impacts, a technology compatibility matrix, and the performance objective functions. An initial population size, which is the number of starting combinations, is also required. The genetic algorithm then acts on the technology combinations and turns individual technologies either on or off depending on the objective function values to identify the final non-dominated set of combinations. The combinations, or portfolios, included in the non-dominated set are referred to as the Pareto-optimal set.

The MOGA MATLAB routines were available at ASDL, so the methodology could be utilized for this research. The 88 technologies previously identified and their corresponding impacts and incompatibilities were input into the MOGA toolset. In Appendix A, the impacts for each technology are provided with three point estimates: the expected value, the absolute minimum value, and the absolute maximum value. For the MOGA implementation, the expected, or mid, values were utilized.

Objective functions are also required to implement MOGA. For this problem, the objective functions are fuel burn reduction, NOx emissions, and the noise margin for the LTA aircraft. Since MOGA may require a large number of function evaluations, the previously defined ANNs were utilized to decrease the computational effort. The three objectives were equally weighted in the MOGA implementation and the initial population size was set to 1,500 technology portfolios.

After implementing MOGA, the initial population converged to 884 non-dominated solutions. Figure 53 displays the objective values for each of the non-dominated solutions. Recall again that these metrics were calculated assuming the mid value impacts for each technology. Therefore, none of the technology performance uncertainty is considered when forming these non-dominated solutions and the results are purely deterministic. The overall best expected performance is approximately 40% fuel burn reduction, 34dB noise margin, and 72.5% NOx emissions reduction. However, these performance values cannot be simultaneously achieved due to performance trade-offs.

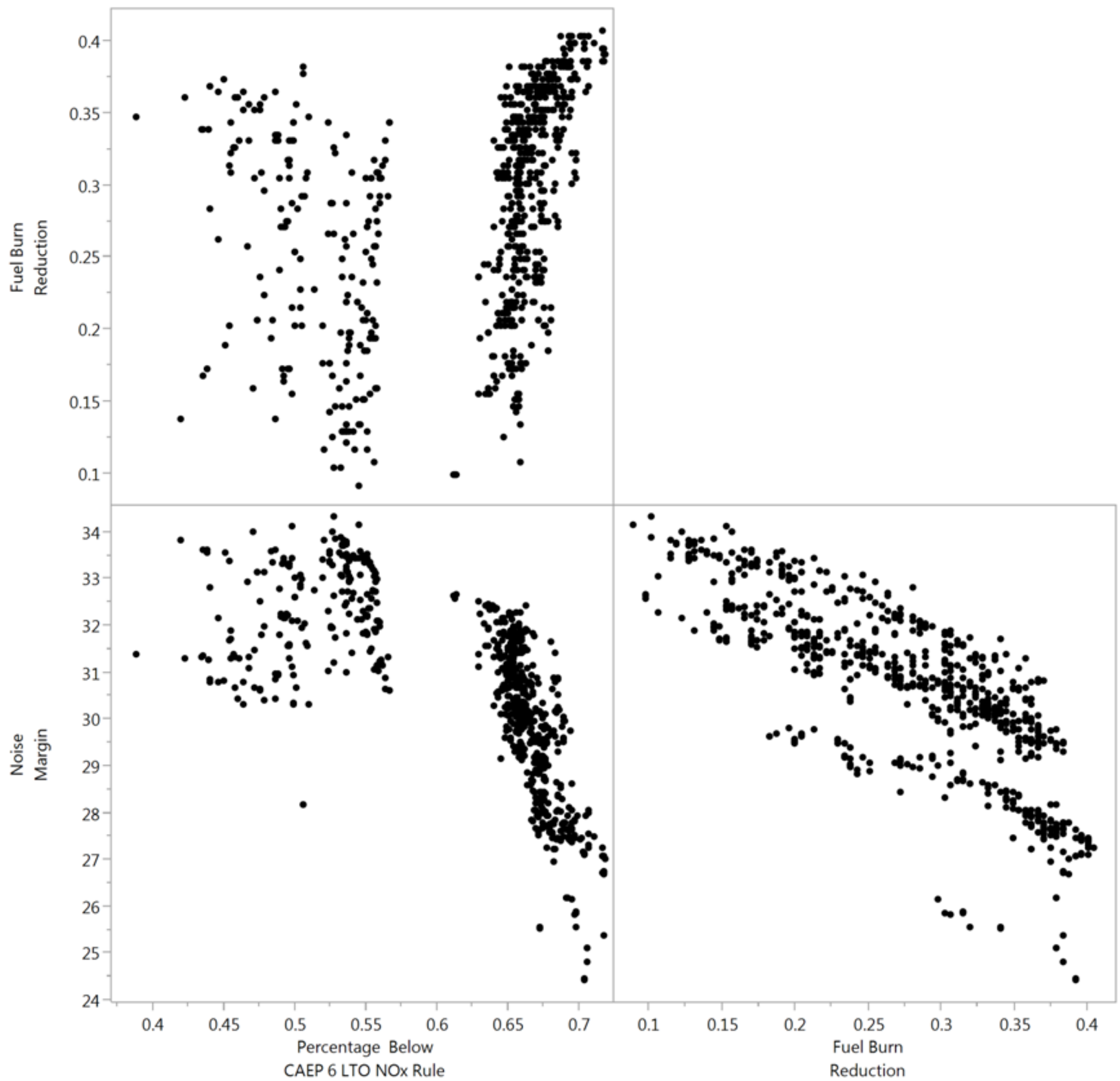

Figure 53: Objective values of non-dominated solutions for MOGA implementation on LTA vehicle.

Several observations were made regarding the MOGA implementation results. First, it was observed that there is a clear gap created in the solutions by the NOx emissions objective. A comparison of the portfolios that provided the best NOx performance to the poor performing NOx portfolios identified that technology T22.1, a compressor intercooler technology, is providing the NOx performance jump. When T22.1 is included in a portfolio, it provides a large beneficial improvement.

The next observation involves the number of technologies included in the resulting portfolios. The MOGA approach is guaranteed to provide technology portfolios with desirable performance that balance the three separate objectives. However, the resulting portfolios include up to 30 non-baseline technologies per portfolio. Due to the cost and time associated with developing technologies, it is unlikely that a program would be able to invest in a portfolio with 30 technologies. For example, Phase 2 of the ERA program involves investment into only eight technologies.

The number of technologies included in each portfolio led to the conclusion that none of the technology portfolios the MOGA approach identified would be viable. The results of the MOGA analysis still, however, provide useful information. If a technology is utilized in a majority of the non-dominated solutions it may be indicative that it provides potentially desirable performance to the aircraft system. In contrast, if a technology is not heavily utilized it may provide system level performance that does not impact the performance goals. Figure 54 provides a comparison of the overall utilization of each of the 88 technologies in the superset. Technologies at the top are the ones utilized the most and technologies near the bottom are ones that were minimally utilized. The technology appearing in the largest number of solutions is T54,Compound Rotor Sweep, with 882 total solutions. T36.5 + T38, Polymer Matrix Composites on the low pressure compressor (LPC) stator, is the technology utilized the least. It was present in only one of the non-dominated solutions.

The information provided by Figure 54 can be used to further prioritize technologies based on the number of additional portfolios they are included in. However, it was observed that T22.1 is a key technology for meeting the provided NOx objective and it only appears in approximately half of the MOGA identified technology portfolios. THerefore, it is difficult to use the technology count information to determine which performance obejctive a single technology is effecting and by how much.

5.2.1.3 Portfolio Formulation based on Objectives

The identification of technology portfolios based upon the performance objectives requires knowledge on how each of the technologies individually affect the goal metrics. In essence, a sensitivity analysis on the goals with respect to the technologies is required. It was previously demonstrated that sensitivity analysis techniques enable the identification of key variables that drive the performance metrics. However, dealing with technologies is different in nature because they are binary, either on or off, whereas the variables are continuous. Therefore, a different type of sensitivity analysis was required.

A type of sensitivity analysis that is conducive to the binary nature of the technology sensitivity problem was identified in the literature. This sensitivity method is referred to as one-at-a-time (OAT) experiments. OAT experiments occur when the impact of changing the values of each factor is evaluated in turn[91]. Since factors are analyzed by themselves, OAT experiments do not enable estimates of interactions among factors and are therefore considered a type of local sensitivity analysis.

OATs alter factors from pre-defined standard conditions. When all factors are at their standard condition, this is referred to as the control scenario. There are different types of OAT experiments but the most basic is the standard OAT. Standard OATs vary one factor from their standard condition while leaving all others at their standard condition. Other types of OATs include the strict OAT and the paired OAT. The strict OAT does not reset all factors back to the control scenario before each new experiment. Rather, a different factor is varied from the condition of the previous experimental run for each proceeding run. Paired OATs produce two observations that result in one simple comparison at a time.[91]

A basic OAT was utilized to identify the impact each technology has on the performance objective metrics. The control scenario was set to the LTA 2010 baseline vehicle and each OAT experiment involved the addition of a single technology from the technology superset. This created a total of 88 OAT experiments, where each contains the 20 baseline technologies plus a single non-baseline technology. The impact of each non-baseline technology on the performance as then determined by comparing the simulation results of each OAT experiment to the 2010 baseline performance values. In instances where a non-baseline technology was incompatible with a baseline technology, the conflicting baseline technology was turned off.

Analyzing each OAT experiment could be done in a purely deterministic manner or by incorporating the uncertainty surrounding the technology impacts. If a deterministic assessment is desired, the mid values for each technology impact are used to define the EDS simulation inputs. The simulations are then conducted and the performance values are recorded. If a probabilistic assessment is desired, all impact information is utilized to formulate probability distributions for simulation inputs. Next, the uncertainty must be propagated to the performance metrics, which is achieved by utilizing the Monte Carlo simulation and surrogate model approach discussed in Chapter Three. Summarizing statistics can then be calculated for the performance objectives and used to demonstrate the impacts of the technologies.

For the implementation of this approach, a probabilistic assessment was conducted. For the purpose of simplicity, uniform distributions were utilized to represent the technology impacts. The lower bound of each distribution was set by the minimum possible value of the impact and the upper bound was set by the maximum possible value of the impact. Since the 2010 baseline technologies are assumed to have reached TRL 9 and they have no uncertainty related to their impacts, the only uncertain variables for each simulation should be the impacts related to the single non-baseline technology. The uncertainty was propagated by utilizing the previously discussed ANNs to conduct a 10,000 case Monte Carlo simulation for each OAT experiment.

The performance results of the 10,000 cases for each OAT experiment were reduced by calculating the means for each of the three objective metrics. The mean values are then used to represent the performance of each OAT experiment. The impact of each technology was then calculated by subtracting the 2010 baseline performance values, shown in Table 11, from the OAT experiment results. These values will be referred to as the performance deltas for each of the 88 non-baseline technologies. The performance deltas of each technology for the three objectives are depicted in Figure 55.

Positive deltas indicate a technology will positively impact a performance objective while negative deltas are indicative of degrading vehicle performance. Negative deltas occur because technologies are represented by detrimental impacts as well as beneficial impacts. Additionally, due to the correlation that exists among the three performance objectives some technologies can negatively impact one objective while positively impacting a different one. The top ten technologies for each objective and their impact on the objectives are provided in Table 22. It is recognized that T22.1 appears as the technology positively impacting NOx emissions the most. This confirms the observations made from the MOGA assessment. Furthermore, it is observed that all of the k-factors T22.1 is mapped to appear in the ANOVA results for NOx emissions.

Table 22: Top ten technologies for each performance objective.

Fuel Burn Reduction		Noise Margin		NOx Emissions Reduction	
Tech	Impact	Tech	Impact	Tech	Impact
T69.2	4.57%	T41	3.80 dB	T22.1	12.98%
T69.1	4.55%	T42	3.37dB	T29.1+T31	1.18 %
T10.2	4.02 %	T57	2.92dB	T20	0.96 %
T68	3.75%	T54	2.00 dB	T83.1	0.94%
T10.1	2.74 %	T53	1.87dB	T83.2	0.62
T22.1	2.42%	T52	1.69dB	T10.1	0.62 %
T11.2	2.35%	T40	1.37dB	T68	0.58 %
T3.1	2.33 %	T56	1.31dB	T6	0.54%
T80.2	2.31%	T83.3	0.63dB	T12.2	0.52 %
T84.2	2.30 %	T83.1	0.59dB	T25	0.51%

The results of this analysis provide a ranking, or prioritization, of the technologies for each of the three performance objectives. This information could be used to reduce the number of technologies under consideration based upon the provided performance deltas. Technology portfolios could then be assembled by creating different combinations of the highly prioritized technologies. Additional information, such as the limiting factor on the maximum number of technologies per portfolio and the incompatibilities among the high priority technologies, would be required to aid the formulation process.

5.2.1.4 Technology Portfolio Formulation Observations

The approaches for technology portfolio formulation discussed and demonstrated in the previous subsections utilized different assessment techniques and information to prioritize technologies and aid technology portfolio formulation. It was observed that the approach outlined by Hypothesis 2.1, where technologies are prioritized based upon how they map to component and subsystem level impacts, did not provide enough of a performance-based prioritization.

The prioritization information provided by the MOGA results is based on the number of times a single technology is included in the non-dominated solutions. The underlying assumption with this is that inclusion of a technology by the algorithm indicates desirable performance. However it was observed that information regarding technologies that drive a single performance metric, such as T22.1 for NOx emissions, may not be easily extracted. Therefore, additional information that does provide explicit performance information may be desired.

The last approach was the use of OAT experiments to determine the independent impact each technology has on the three performance objectives. It was demonstrated how the information provided by the OAT experiments can be used to prioritize technologies. This prioritization is based explicitly on performance information and considers both beneficial and detrimental effects the technology may have during prioritization.

These observations led to the formulation of the *Form Technology Portfolios* process provided in Figure 52. It is believed that the results of the first presented method, prioritizing technologies based upon how they map to important metrics could be used as either the first phase of a performance-based technology prioritization of to aid technology identification. For thsi research a set of relevant technologies were provided. However, it is acknowledged that this may not always be the case for future technology development programs. Therefore, the informaiton provided by the key impacts and the impact scenarios gives decision makers an idea for what capabilities they should pursue and how much of a single capability improvement is required. Once the initial set has been identified, the decision makers can determine if a reduction, or further prioirtization, is requried. It was demonstrated that further performance-based prioritization can be acheived through the OAT analysis technique. The number of technologies included for technology portfolio formulation would be dependent on the number of technologies per portfolio and the computational resources available to the program.

This experimental results and observations and the final process provided in Figure 52 partially support Hypothesis 2.1. Therefore, the final answer to Research Question 2.1 is as follows:

System-level sensitivity analysis information for each technology under consideration paired with the mapping of technology impacts to important low level metrics of a physics based modeling and simulation environment that captures the performance objectives enables sets of potentially viable technology scenarios to be identified.

5.2.2 Technology Portfolio Evaluation and Selection

After a set of potential technology portfolios have been formulated, they must be analyzed to provide information that enables comparisons, trade-offs, and down-selection. Hypotheses 2.2 and 2.3 outlined sets of information that would adequately characterize readiness risk and performance risk respectively. Each involves measures of likelihood and measures difficulty that must be calculated. After the technology portfolios are assessed, the decision maker would have to select a single portfolio to pursue. If the selected portfolio does not expend all of the program's resources, supplemental technologies could then be selected, which is addressed through Hypothesis 2.4. Figure 56 provides the final process formulated for *Evaluate and Select Technology Portfolio*. It involves several new analysis techniques that will be outlined in the proceeding sub-sections that enable the calculation of the hypothesized risk measures.

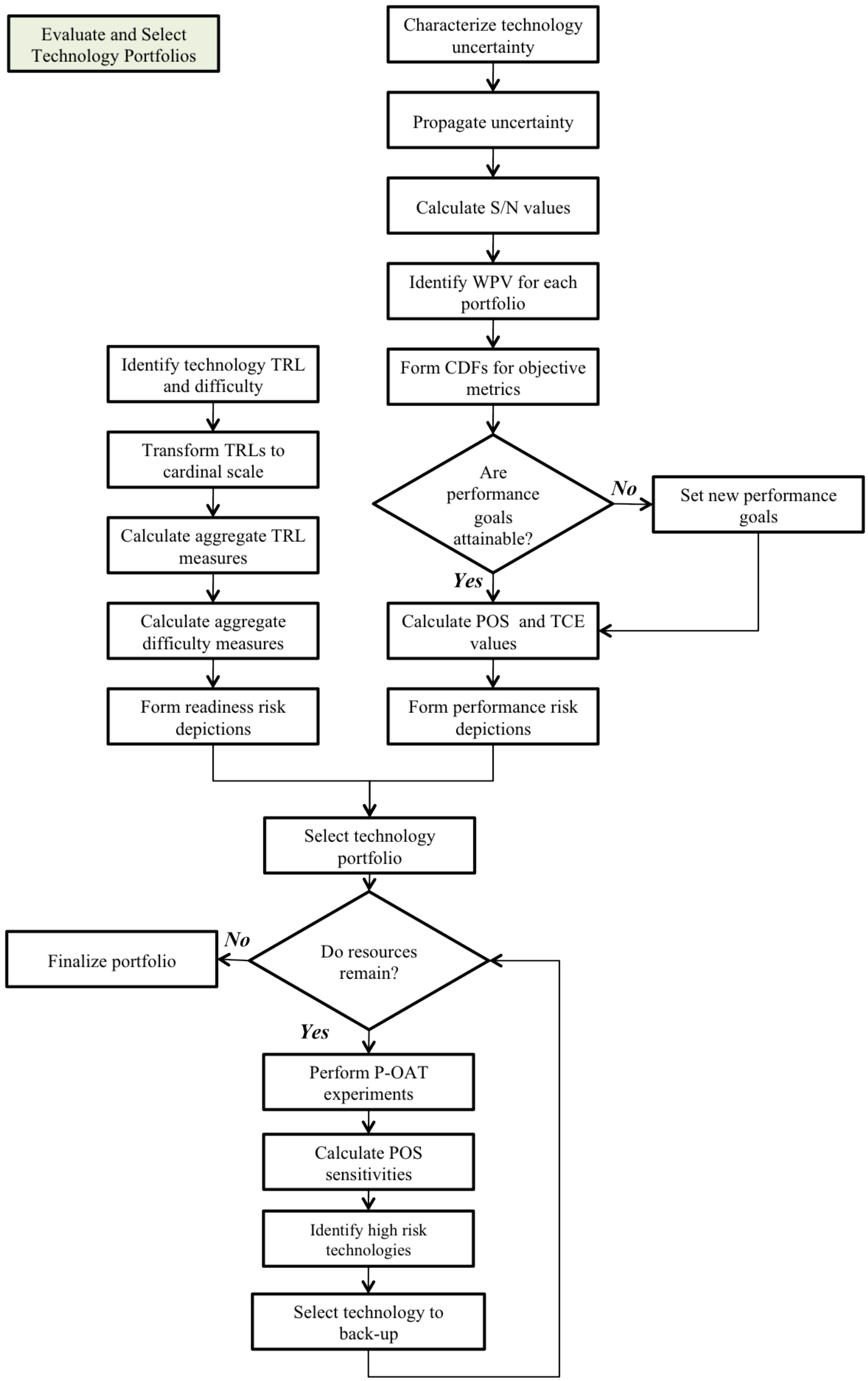

Figure 56: Process flowchart for technology portfolio evaluation.

The remaining portion of Experiment Set 2 expands on how the process outlined in Figure 56 was formulated and examines the capability of the proposed value measures to communicate readiness and performance risk. This portion of the experiment required a set of technology portfolios to analyze and compare. The informaiton provided in the previous section regarding technology portfolio formulation was utilized to form twelve different technology portfolios of eight technologies each. All of the information provided by the two layers of prioritization was used to demonstrate how technology portfolios can be formed. The technologies included in the portfolios were selected based on their contribution to a single objective metric. The resulting technology portfolios are described in Table 23.

Table 23: Technology portfolio definition for Experiment Set 2

Portfolio Number	Technologies
Portfolio 1	T42, T52, T54, T69.1, T10.2, T68, T22.1, T53
Portfolio 2	T52, T54, T56, T69.1, T10.2, T68, T22.1, T40
Portfolio 3	T52, T54, T57, T69.1, T10.2, T68, T20, T53
Portfolio 4	T42, T52, T54, T10.1, T10.2, T68, T20, T40
Portfolio 5	T52, T54, T56, T10.1, T10.2, T68, T22.1, T53
Portfolio 6	T52, T54, T57, T10.1, T10.2, T68, T22.1, T40
Portfolio 7	T42, T52, T54, T69.1, T3.1, T68, T20, T53
Portfolio 8	T52, T54, T56, T69.1, T3.1, T68, T20, T40
Portfolio 9	T52, T54, T57, T69.1, T3.1, T68, T22.1, T53
Portfolio 10	T42, T52, T54, T10.1, T3.1, T68, T22.1, T40
Portfolio 11	T52, T54, T56, T10.1, T3.1, T68, T20, T53
Portfolio 12	T52, T54, T57, T10.1, T3.1, T68, T20, T40

5.2.2.1 Readiness Risk Analysis

For readiness risk, it was established that TRL would be for the measure of readiness for an individual technology. However, this phase requires a measure of readiness to represent the readiness of the entire technology portfolio. There are two different ways this could be done. First, the readiness could be represented by a single technology's TRL, such as the lowest TRL present in a given portfolio. The underlying assumption with this approach is that the readiness of the portfolio cannot be higher than the readiness of its technologies. However, if all technologies except for one are at a high readiness level this could be misleading. The second approach is to create an aggregate measure of readiness utilizing the cardinal TRL scale presented in Table 5. This scale could be used to augment the technology TRLs and facilitate the mathematical combination of the individual values.

Both approaches were implemented for the readiness risk analysis. For the aggregate measures, the provided TRL for each technology shown in Appendix A was augmented using the cardinal TRL scale. Next, different statistics were calculated based upon the new TRL values of each technology within a given technology portfolio. The statistics calculated were the mean TRL, variance of the TRLs, and sum of the TRLs. Note that these statistics include the 2010 baseline technologies on the vehicles, which are all at TRL 9.

Next, the difficulty aspect of readiness risk was investigated. The measure of difficulty used for this research should capture readiness likelihood. Therefore, it needs to characterize how difficult it will be for a technology to increase its current readiness level to the required readiness level. Metrics like R & D^3 and AD^2 were mentioned, but it was established that neither are a perfect fit for this purpose and both lack an executable calculation process.

Based on these observations and the information available for each technology, a new way to represent difficulty was formulated. It has been acknowledged in the literature that time and money are both surrogates for effort expended. Furthermore, when a large amount of effort, or long amount of time, is required to mature a technology, it can be assumed the technology is difficult to mature. Therefore, the time to mature and the difficulty to mature are analogous and can be used interchangeably.

It was established that the number of years until TRL 9 is achieved is provided in Appendix A for each technology. Therefore, this information was used to represent difficulty for each individual technology. Now, similarly to the measure of readiness, the difficulty of an entire portfolio can be represented by either an aggregate measure or the highest individual difficulty observed. Aggregate measures of difficulty were calculated by mathematically combining the data for each technology within a given portfolio. The measures calculated were the maximum amount of years, the sum of the years, and the mean year.

The calculated measures for readiness risk resulted in nine different potential risk depictions. These depictions are provided in the form of scatterplots shown in of Figure 57. The difficulty measures are provided on the y-axis and for each the goal is to minimize the values for low risk. In contrast, the likelihood values are shown on the x-xis and the goal for each is to maximize all of the values for low risk. Therefore, for each subfigure in Figure 57 the low risk portfolios are in the bottom right corners. Identification of the areas of high risk and low risk is aided through the use of risk matrix color coding, where red signifies high risk, yellow signifies medium risk, and green signifies low risk. For the risk depictions provided in this research, the assignment of the green/yellow/red areas was done subjectively to aid risk visualization. However, in a real-life implementation decision makers would need to determine the appropriate risk thresholds if this type of depiction was to be utilized.

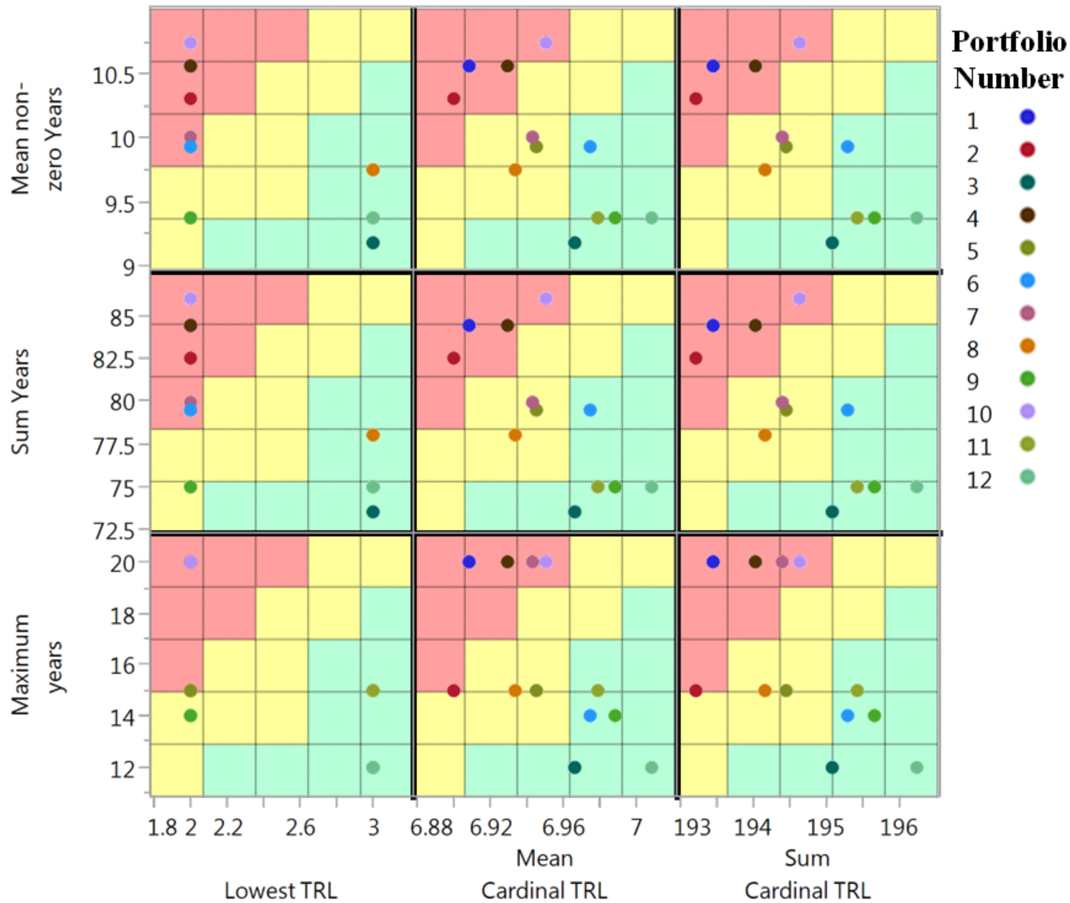

Figure 57: Readiness risk comparison plot.

5.2.2.2 *Performance Risk Analysis*

The first step of the performance risk analysis process was to characterize the uncertainty with probability distributions. Previously in this research, only uniform distributions have been used. For this phase, the use of triangular distributions was explored. Triangular distributions are defined by three points: the minimum value, the maximum value, and the most expected value. Recall that the impact information provided for each technology in Appendix A is in the form of a 3-pt estimate. Therefore, the use of the triangular distributions was straightforward.

The uncertainty was propagated to the system level for each of three objective metrics using a 50,000 case Monte Carlo analysis with the previously defined ANNs.

The ANNs defined for the objective metrics are still relevant because the ranges for the input variables defined by the technology portfolios are within the initially defined ranges. This process was completed for each of the twelve technology portfolios.

The resulting probabilistic performance of the twelve portfolios is summarized through Figure 58 and Figure 59 with a comparison of the variances and means, respectively. In general, it is desired to have a technology portfolio with good expected performance and low amount of uncertainty. While these figures enable identification of portfolios that provide one characteristic or the other, they do not enable a comparison of both simultaneously.

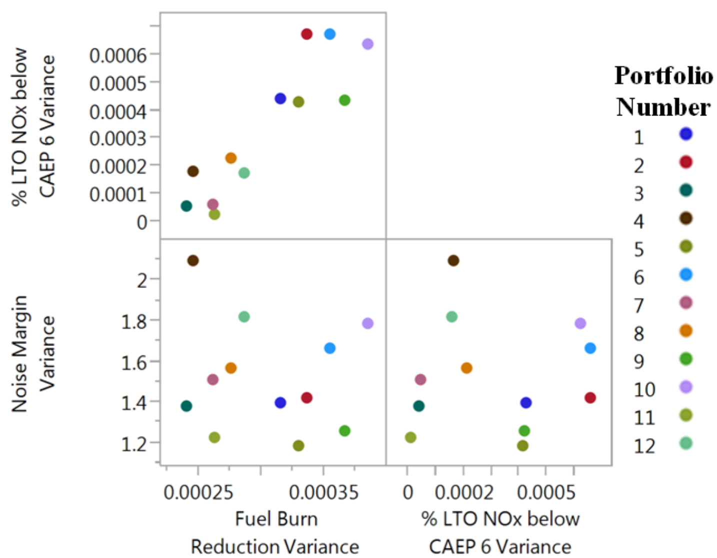

Figure 58: Comparison of variance for fuel burn reduction, noise margin, and NOx emissions.

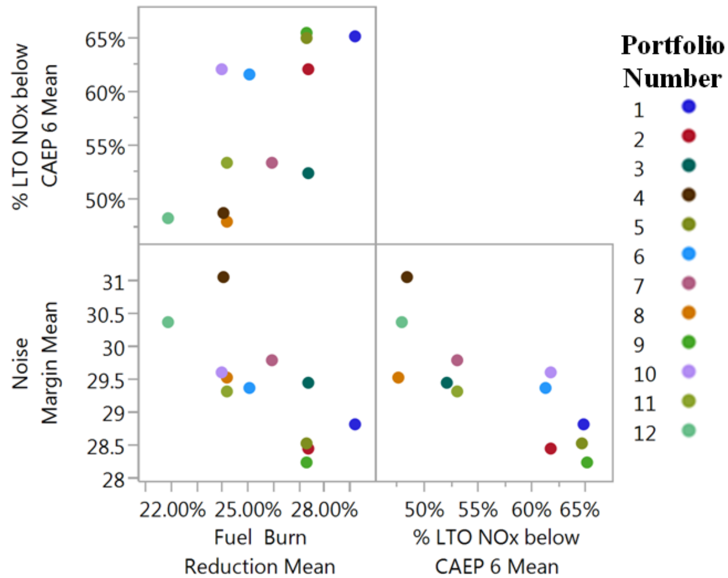

Figure 59: Comparison of means for fuel burn reduction, noise margin, and NOx emissions.

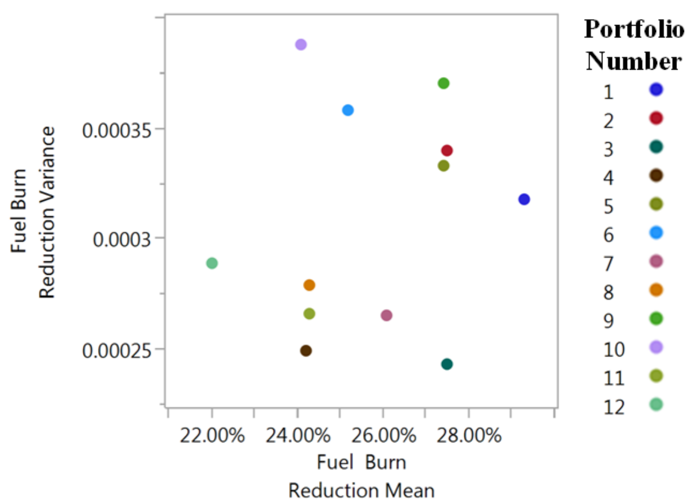

Figure 60: Fuel burn reduction Mean vs. Variance of technology portfolios

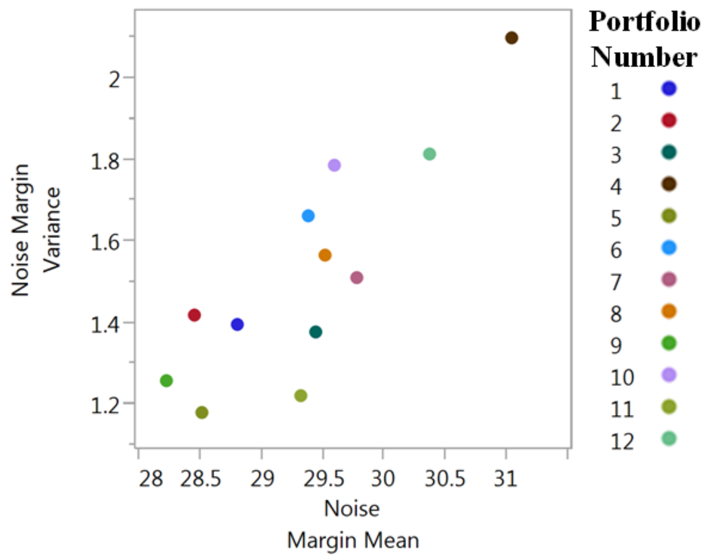

Figure 61: Noise margin Mean vs. Variance of technology portfolios

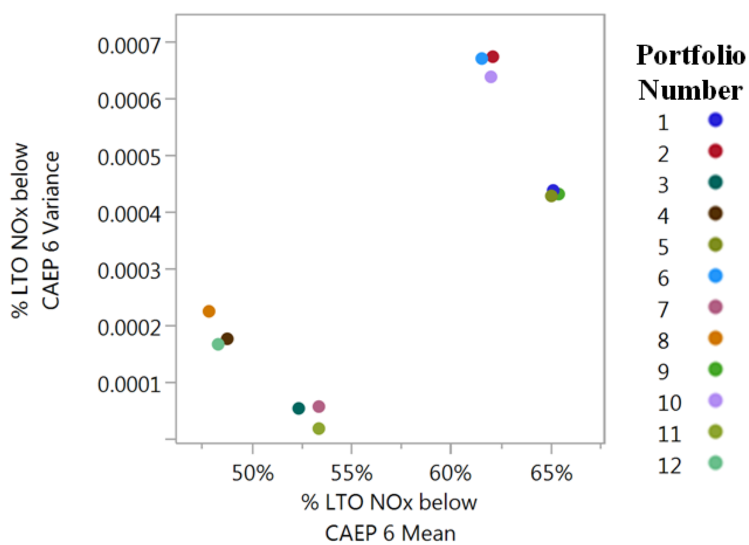

Figure 62: NOx emissions Mean vs. Variance of technology portfolios

Figure 60, Figure 61, and Figure 62 provide the results of the probabilistic analysis but in a different form. Instead of comparing means and variances separately, they are now plotted against each other for each of the three objective metrics. Scenarios that display favorable performance are the ones closest to the bottom right of each subplot. For fuel burn reduction, Portfolio 3 is closest to the bottom right corner and has the best performance with respect to variance. However, it does not have the best mean performance. Portfolio 1 has the best mean performance but is ranked seventh with respect to variance.

For noise margin, the bottom right corner is not populated at all, which implies there are no portfolios that excel with respect to both mean and variance. Portfolio 5 has the best variance, but is ranked tenth with respect to mean. Portfolio 4 has the best mean but is ranked last with respect to variance. For NOx emissions, the bottom right corner is again vacant. Portfolio 11 has shows the best variance, but is ranked eighth with respect to mean. Likewise, Portfolio 9 has the best mean performance but is ranked eighth with respect to variance.

Recall, it was suggested in Chapter Four that both mean and variance could be pursued as measures of likelihood for performance risk. The results displayed in Figures 60-62 lead to the conclusion that these measures would provide drastically different risk rankings. Additionally, it is felt that use of only one of these would not be sufficient to communicate the information resulting from the probabilistic performance analysis with respect to performance likelihood. Therefore, before proceeding with the calculation of the remaining performance risk measures the use of a newly identified performance measure was explored.

It was discovered in the literature that there is a measure commonly used in the field of signal processing that provides a synthesis of expected performance and variation or uncertainty in the response. This measure is called the signal-to-noise ratio (S/N). S/N ratio was invented by Genichi Taguchi to aid selection between noisy processes. It provides a dimensionality reduction that enables the comparison of options with respect to expected performance and variability simultaneously through a single metric.

S/N is a function of the mean squared deviation (MSD). MSD is a metric captures the variability and shifting of the target of a dataset by assuming a quadratic loss function. Calculation of MSD depends on the nature of the objective metric. If the goal is to maximize the objective metric, the MSD is calculated with Equation (50) where n is the number of samples and y_i are the sampled metric values. Likewise, when the goal is to minimize the objective value, Equation (51) is utilized. Finally, when the goal is for the objective to hit a target or nominal value, and Equation (52) is utilized where T represents the target value.

$$MSD = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2} \tag{50}$$

$$MSD = \frac{1}{n}\sum_{i=1}^{n}y_i^2 \tag{51}$$

$$MSD = \frac{1}{n}\sum_{i=1}^{n}\left(T - y_i\right)^2 \tag{52}$$

For each of the three described goal scenarios, a small value of MSD corresponds to desirable expected performance and minimal variation. Next, S/N is introduced to alter the data through the use of a logarithmic transformation. S/N is calculated through Equation (53). Now, favorable alternatives are identified by large values of S/N.

$$S/N = -10log_{10}\left(MSD\right) \tag{53}$$

The S/N was calculated for all three objective metrics for the twelve technology portfolios under consideration. The results are depicted in Figure 63 which provides comparisons of S/N values of one objective metric against another. Portfolios that manifest in the top right corner of each subplot show desirable characteristics for both objective metrics.

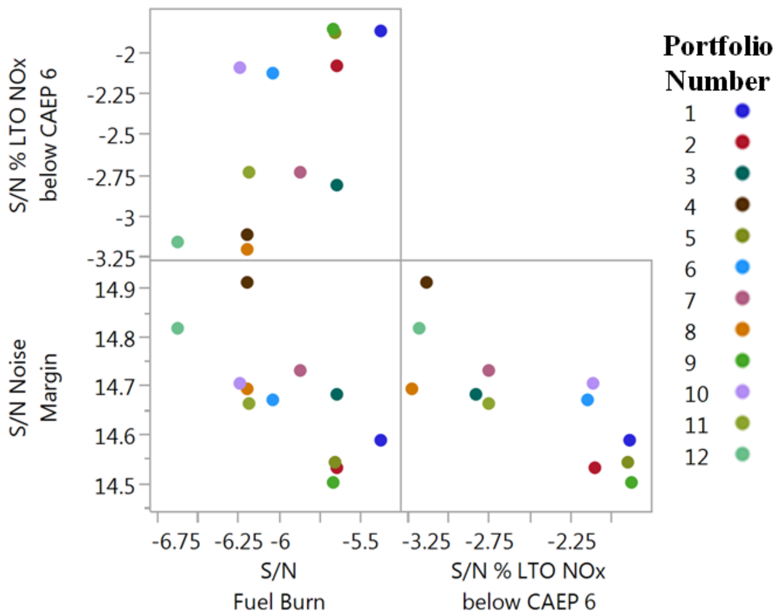

Figure 63: Comparison of S/N ratio for fuel burn reduction, noise margin, and NOx emissions.

S/N provides the desired dimensionality reduction and enables a 3-way comparison of expected performance and variability of all three objective metrics that was otherwise not possible. However, the absolute values of S/N do not provide any insight on what the actual expected performance or variability is for each portfolio. It can only be utilized for comparative purposes. Therefore, while S/N is further considered for the likelihood aspect of performance risk, POS is also still explored.

The POS was calculated by first using the results of the Monte Carlo analyses to formulate the CDFs for each of the three objective metrics. Since all objectives are trying to be maximized, reverse CDFs are used in place of regular CDFS. In a reverse CDF, the the y-axis represents the probability of meeting or exceeding the value on the x-axis. The reverse CDFs for fuel burn reduction are shown in Figure 64, for noise margin in Figure 65, and NOx emissions in Figure 66. For all three figures, portfolios whose reverse CDFs are shifted towards the right have more desirable performance.

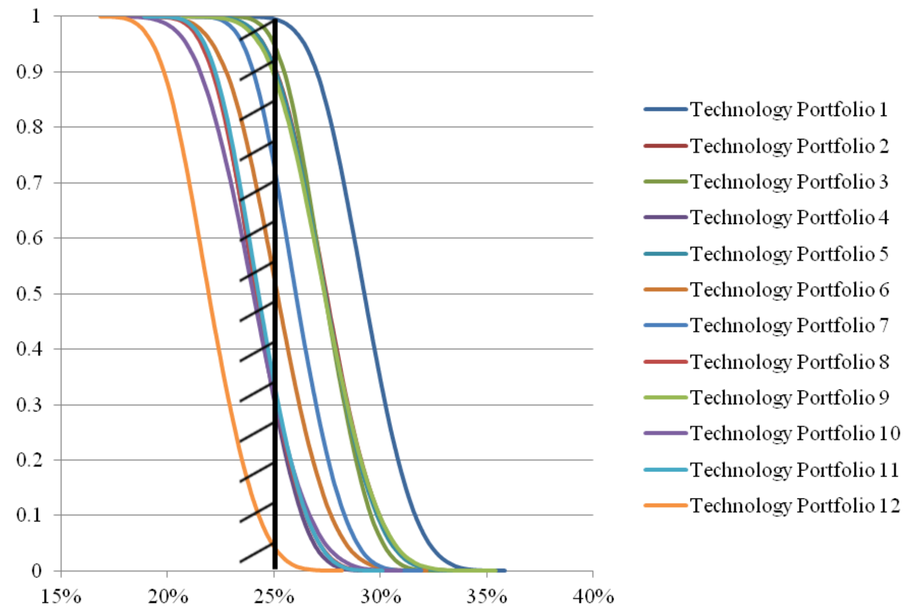

Figure 64: Comparison of fuel burn reduction CDFs.

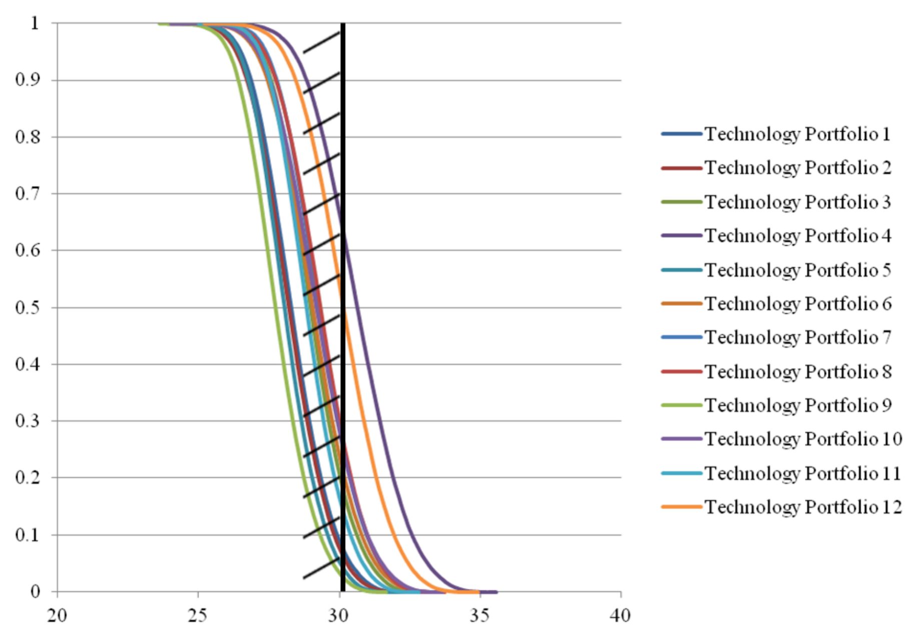

Figure 65: Comparison of noise margin CDFs.

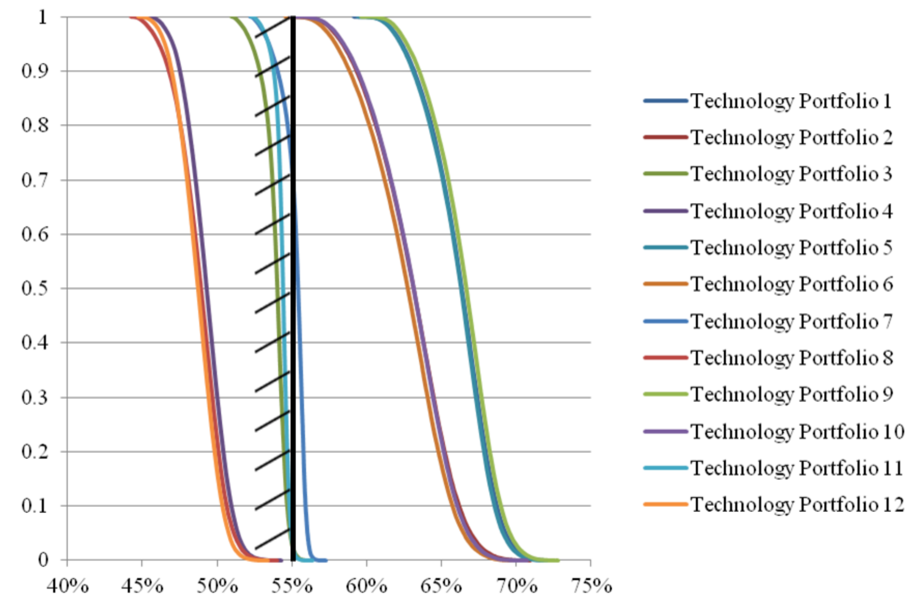

Figure 66: Comparison of NOx emissions CDFs.

The CDFs were used to identify the specific goal values for each objective metric. This is important because a POS cannot be calculated without these values. In the last section a set of goals were enumerated based on the initial ranges set for the impact variables. It was acknowledged that improvements on many impact variables is required in order to meet the set goals. Since each technology portfolio under consideration involves only eight technologies, it is not realistic to expect they can achieve the previously defined goals. This is demonstrated through Figure 67 where the mean performance values for each technology portfolio is overlaid on the forecasted LTA results with the previously set performance goals. It is clear that none of the selected portfolios are able to meet all three goals simultaneously. Therefore, new goals were required to measure the capabilities of the technology portfolios using POS.

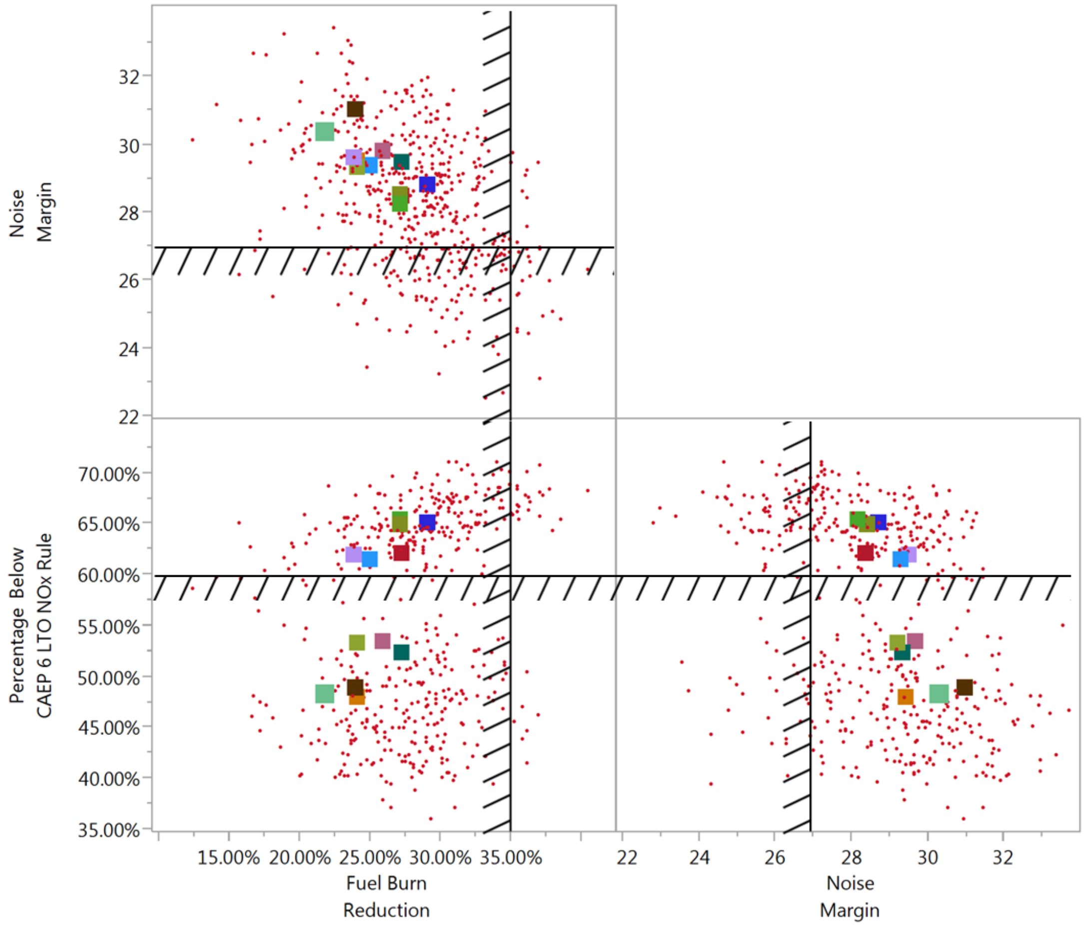

Figure 67: Comparison of technology portfolios to the LTA TIF analysis results.

Information provided by the reverse CDFs was used to set the new goals. It was desired that each portfolio have a non-zero POS for at least one of the three objectives and that each objective can potentially be met by a majority of the portfolios. The new goals are: a fuel burn reduction of 25% relative to the 2010 baseline, a noise margin of 30dB, and a 55% LTO NOx emissions reduction below CAEP 6. After these goals were set, the POS values were calculated for each of the twelve portfolios and are shown in Table 24.

Table 24: Probability of success values for goals set at 15% fuel burn reduction, 35 dB noise margin, and 55% LTO NOx emissions reduction below CAEP 6.

Portfolio Number	Fuel Burn POS	Noise Margin POS	NOx POS
Portfolio 1	99.59%	15.86%	100.00%
Portfolio 2	91.40%	9.62%	99.99%
Portfolio 3	95.11%	33.69%	0.77%
Portfolio 4	31.22%	76.31%	0.00%
Portfolio 5	90.97%	7.76%	100.00%
Portfolio 6	53.11%	32.67%	99.99%
Portfolio 7	73.85%	44.90%	5.36%
Portfolio 8	32.68%	36.23%	0.00%
Portfolio 9	89.47%	4.52%	100.00%
Portfolio 10	31.94%	40.14%	100.00%
Portfolio 11	33.92%	28.40%	0.85%
Portfolio 12	4.36%	61.61%	0.00%

Ideally, a selected technology portfolio would have a high POS for each of the three goals. Figure 68 provides a comparison of POS values for two objectives at a time. Technology portfolios that manifest in the top right corner of each subfigure provide the highest likelihood of meeting the goals. With respect to NOx emissions and fuel burn reduction, Portfolio 1 is easily identified as the the best portfolio; with respect to NOx emissions and noise margin, Portfolio 10 is the best; and with respect to noise margin and fuel burn reduction Portfolio 3 and Portfolio 7 are the best. Again it is recognized that only technology portfolios containing T22.1 have favorable NOx performance.

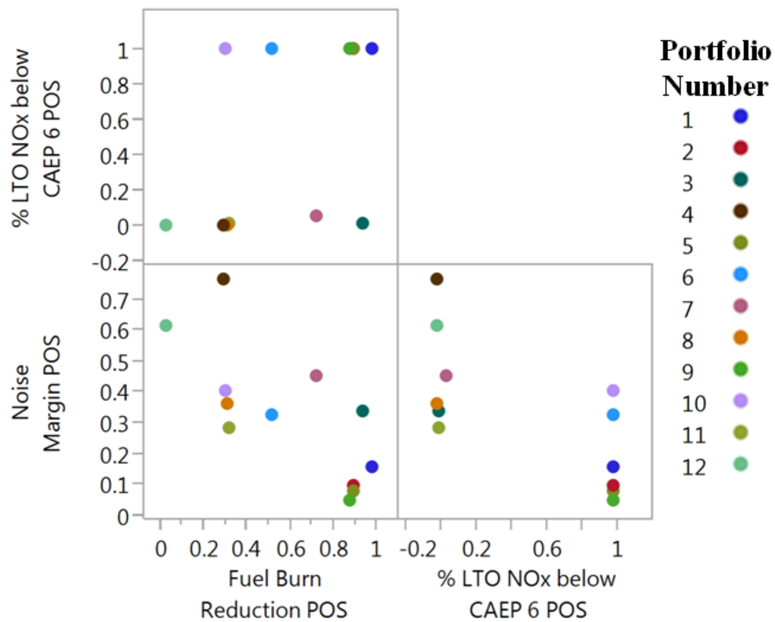

Figure 68: Comparison of probability of success for fuel burn reduction, noise margin, and NOx emissions.

Next, the measures of difficulty for performance risk were calculated. Recall, two different measures were proposed to capture difficulty and they are the tail conditional expectation (TCE) and the worst possible value (WPV). The tail conditional expectations were calculated in a straightforward manner using Equation (21). For each objective metric, the results of each 50,000 case Monte Carlo analysis were filtered to obtain the values that did not meet the defined goals and the mean of these remaining points was then calculated. The WPVs were found for each objective metric by taking the minimum objective values observed in each Monte Carlo analysis. It should be noted that the actual WPV could be worse than the values reported by the Monte Carlo analysis since not all possible input combinations are sampled. However, for the purpose of this research it is assumed to be representative enough.

Once all of the relevant performance risk measures were calculated, the different performance risk depictions were formed. For each objective metric, there are four possible performance risk depictions. The depictions are provided in the form of scatterplot subfigures in Figure 69 for fuel burn reduction, Figure 70 for noise margin, and Figure 71 for NOx emissions. In each of these three figures, the top left subfigure is TCE versus S/N; the top right subfigure is WPV versus S/N; the bottom left subfigure displays TCE versus POS; and the bottom right subfigure displays WPV versus POS. For all four subfigures, the low risk portfolios are in the top right corner. Again, the risk matrix green/yellow/red color coding was utilized to aid risk visualization.

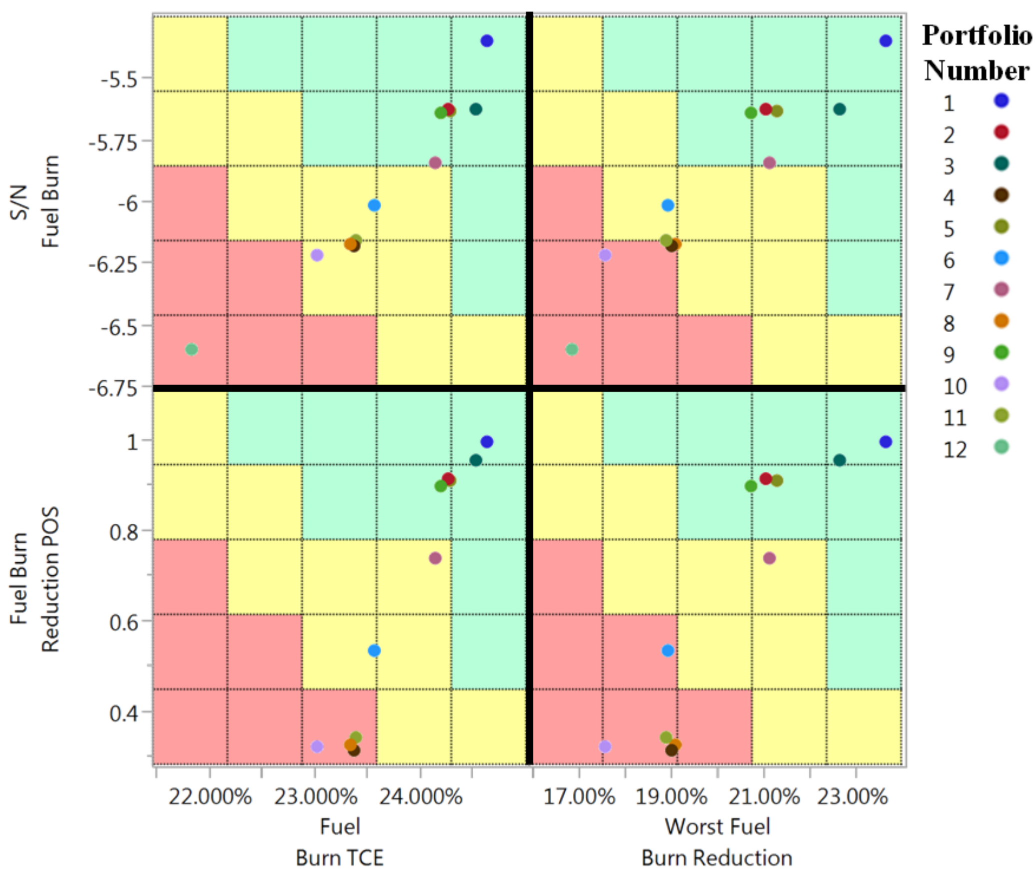

Figure 69: Performance risk plots for fuel burn reduction.

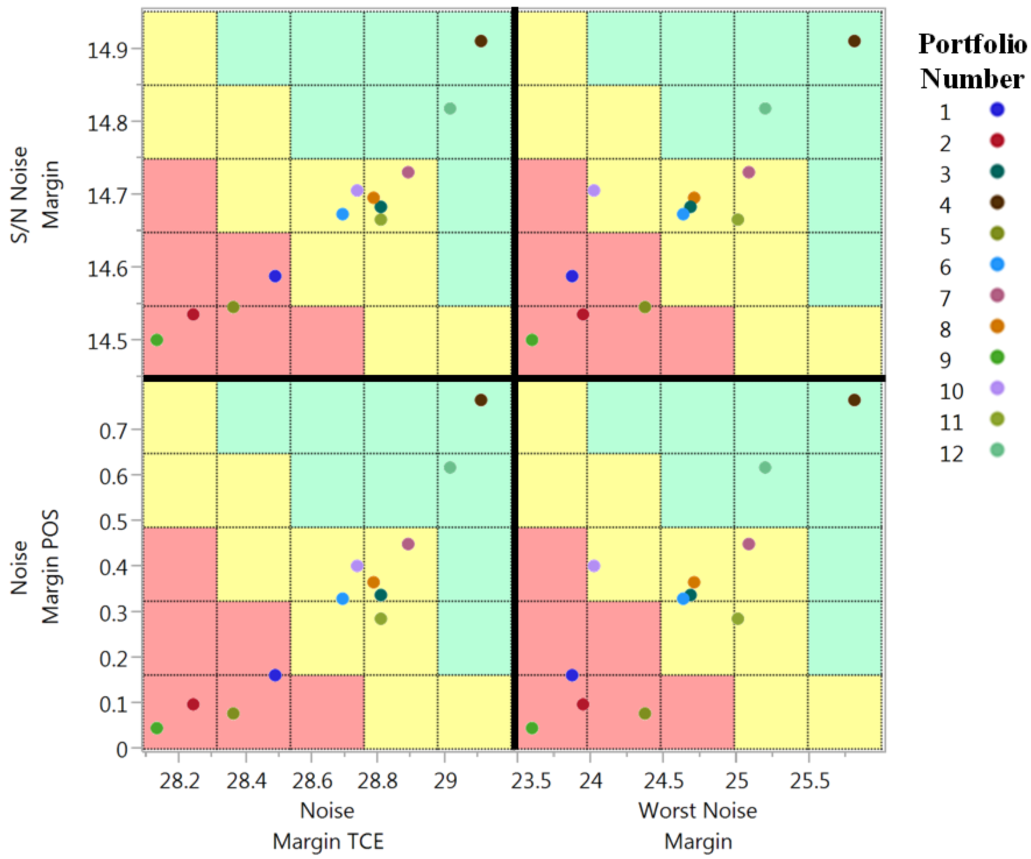

Figure 70: Performance risk plots for noise margin.

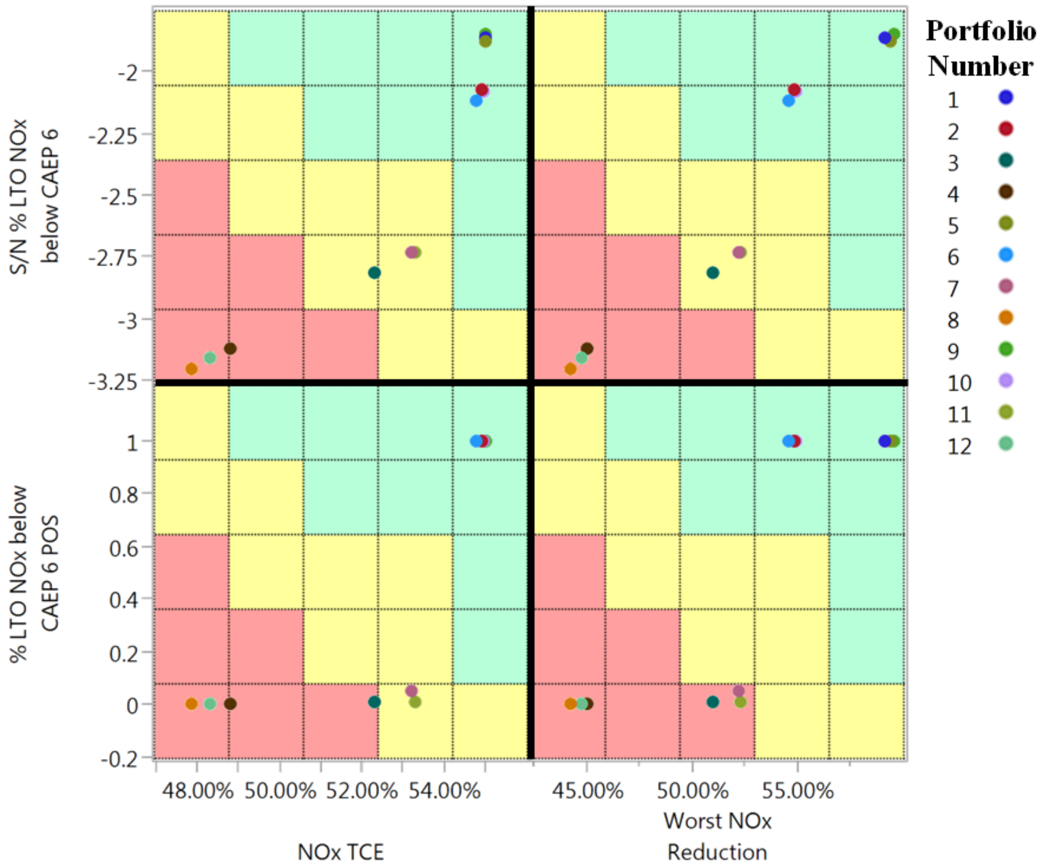

Figure 71: Performance risk plots for NOx emissions.

5.2.2.3 Technology Portfolio Down-Selection

After the proposed measures were calculated, the trends observed in the different sub-figures of Figure 57 were observed. Recall portfolios with low readiness risk should appear in the bottom right corner of each of the sub-figures. The lowest TRL technology for all portfolios is either 2 or 3, which causes the trends for the lowest TRL sub-figures (the left three sub-figures) to be two vertical lines. The mean cardinal TRL and sum cardinal TRL spread the portfolios out along the horizontal axis, which enables more comparisons among the portfolios.

For the measures of likelihood, the maximum years measure displays characteristics similar to those observed for the lowest TRL measure. There are only four different maximum years observed for the twelve portfolios, so the portfolios are concentrated. This is very noticeable in the bottom left sub-figure, lowest TRL versus maximum years. It appears that only five of the portfolios are plotted, but in reality multiple portfolios fall on the same point. While this issue of multiple portfolios having the same values for both risk measures could occur with the other combinations of measures, it is less likely because the other measures are defined by a more-continuous, less-discrete scale. This is observed for the sum years measure and mean years measure because they provide a larger spread in the data, which greatly improves the ability to make comparisons.

It is observed that when the measure of consequence is held constant and the measure of likelihood is changed from the sum years measure to the mean years measure, no change in the sub-figure occurs. Likewise, when the measure of likelihood is held constant and the measure of consequence is changed from sum TRL to mean TRL, no change in the sub-figure occurs. This implies that any combination of the mean years, sum years, mean TRL, and sum TRL will communicate the same trends in the data for these twelve technology portfolios. It is acknowledged, however, that this will not always be the case, especially when technology portfolios under consideration have different numbers of non-baseline technologies. Note that for this example all portfolios have eight non-baseline technologies so it is expected that portfolios with the highest sum values will have the highest mean values for either TRL or years until TRL 9.

The trends for performance risk were analyzed next, starting with fuel burn reduction. Recall, portfolios with the lowest performance risk are in the top right for all subfigures. It is observed that the four subfigures in Figure 69 have similar trends. It was expected that the POS would increase as the TCE or WPV increases, and the observed trends confirm it. Furthermore, the same increasing trends are also observed for S/N versus the two measures of consequence.

The top portfolio with respect to low fuel burn reduction performance risk is quickly identified as Portfolio 1. Portfolio 1 is the only portfolio with a 100% POS of meeting the stated fuel burn reduction performance goal. All portfolios provide a non-zero POS. For noise margin, it is observed that Portfolio 4 has the lowest performance risk and Portfolio 9 has the highest. No portfolios provide a 100% POS of meeting the noise margin goal, but all provide a non-zero POS.

For NOx emissions, Portfolio 1, Portfolio 5, and Portfolio 9 provide the best performance risk. It is observed that POS and TEV do not independently enable comparisons among the top three portfolios because all have a POS of 100%. S/N does, however, provide a spread in the data for scenarios that have a 100% POS. This is apparent when comparing the right two sub-figures. On the bottom, the only spread in the data is due to the horizontal axis, WPV. In contrast, on the top the three portfolios are separated from each other in both the vertical and horizontal directions.

To properly demonstrate how the selection of the risk measures can alter the selection process, an existing multi-attribute decision making(MADM) algorithm was implemented. The MADM method selected for this research is Technique for Order Preference by Similarity to Ideal Solution, or TOPSIS. TOPSIS is based on the idea that the selected alternative should be closest to the positive ideal solution and farthest from the negative ideal solution. The use of TOPSIS requires the assignment of weights to the different attributes under consideration. The results of TOPSIS are given in the form of a normalized distance, where the most attractive alternative will have the largest distance.

TOPSIS was implemented on the risk analysis results for the twelve portfolios. For performance risk, TOPSIS was implemented once for each of the four combinations of likelihood and consequence measures. The different objective metrics were not separated for their own analysis and instead were combined so the effects of each performance goal would be considered. Therefore, for each performance risk TOPSIS analysis there were six attributes considered, a measure of likelihood and a measure of consequence for each of the three objective metrics. The weightings of the attributes were assumed to be equal.

The results of the performance risk TOPSIS analysis are shown in Figure 72. The bar charts plot the TOPSIS-calculated distances, where alternatives with distances closest to one are top-ranked and have the lowest performance risk. For all scenarios except POS vs. WPV, Portfolio 1 was identified as the best. For POS vs. WPV, Portfolio 6 was identified as the best. Portfolio 12 was identified as the worst for S/N vs. TCE and S/N vs. WPV, while Portfolio 11 was identified as the worst for POS vs. TCE and POS vs. WPV.

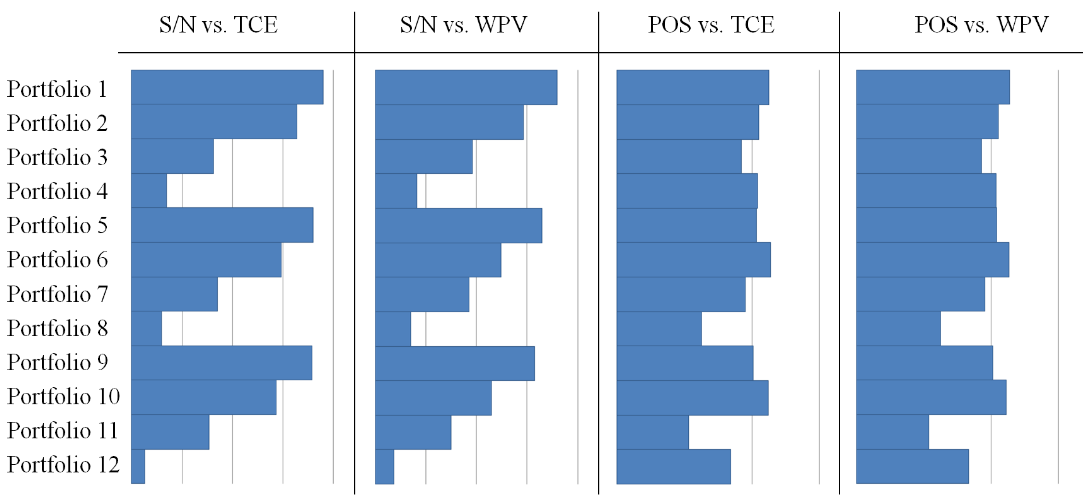

Figure 72: TOPSIS-calculated distances for Performance Risk decision scenarios.

For readiness risk, TOPSIS was implemented once for each of the nine potential combinations of risk measures shown in Figure 57. For each implementation, there were only two attributes and they were equally weighted. The results are shown in Figuire 73, Figure 74, and Figure 75. The results of the TOPSIS analysis for readiness risk do not provide any surprising results. As previously discussed, the results shown in Figure 57 are fairly straightforward. The risk information for readiness risk is easily communicated through the use of a single figure, whereas this proved difficult for performance risk due to the three different performance goals. Therefore, based on previous observations, it is not surprising that the results displayed in Figure 74 and Figure 75 are exactly the same.

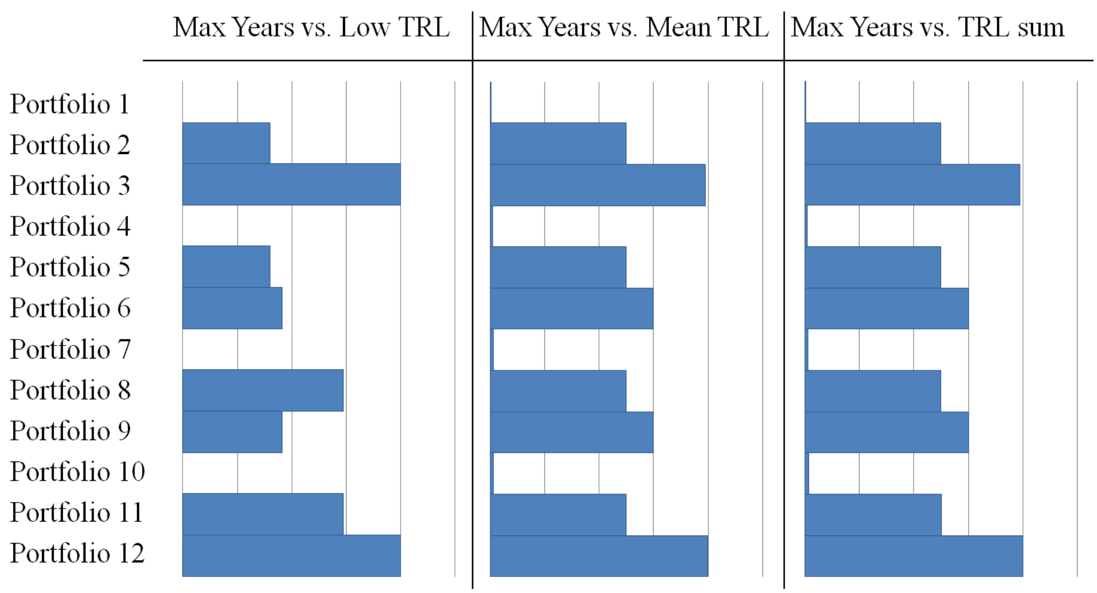

Figure 73: TOPSIS-calculated distances for Readiness Risk scenarios with maximum year as the likelihood metric.

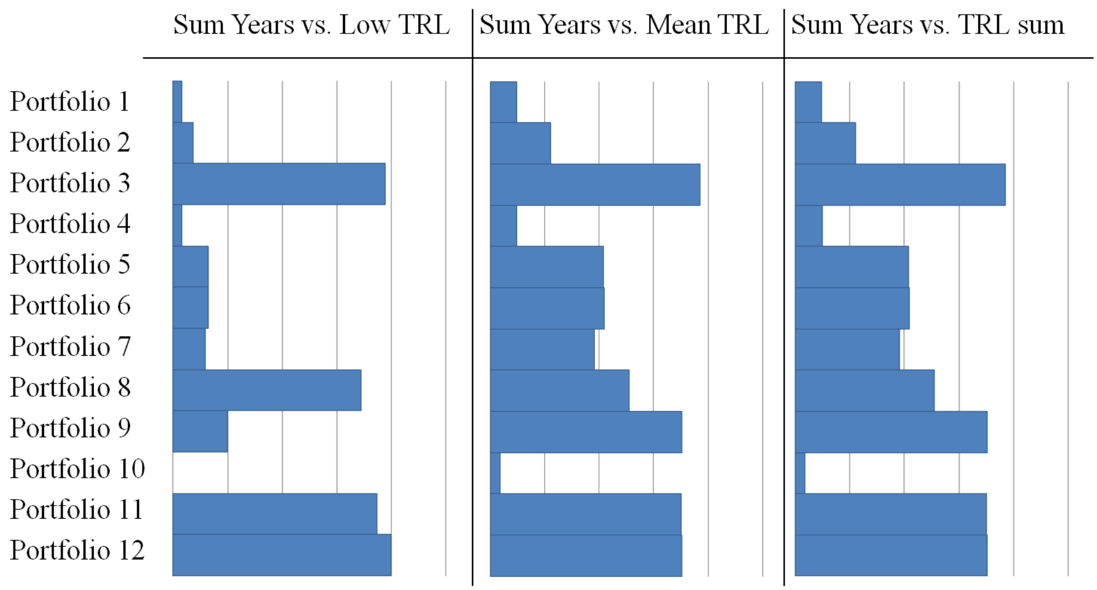

Figure 74: TOPSIS-calculated distances for Readiness Risk scenarios with sum of the years as the likelihood metric.

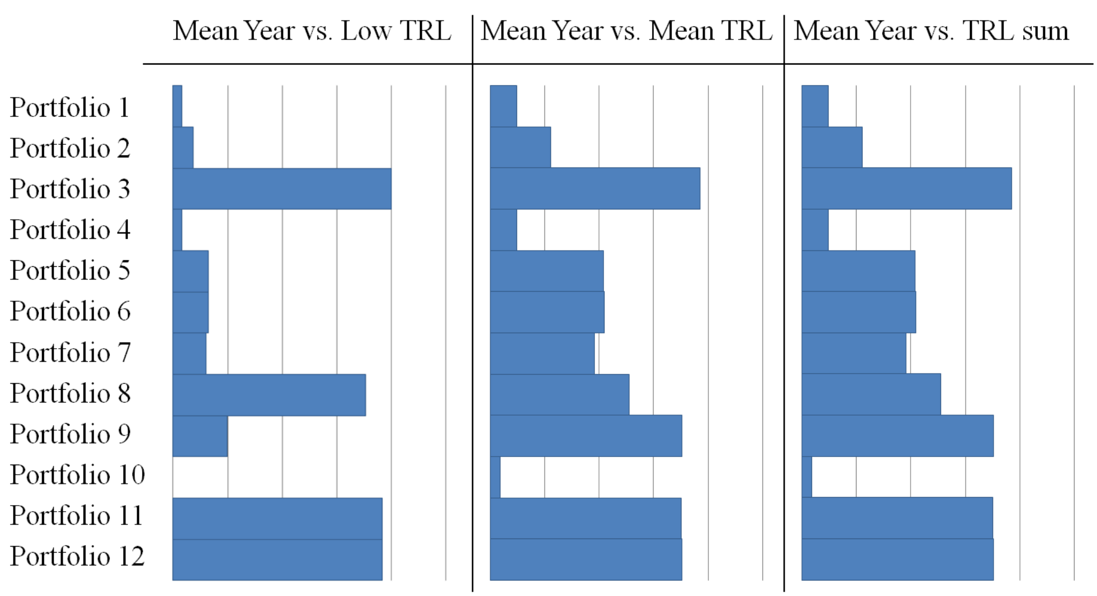

Figure 75: TOPSIS-calculated distances for Readiness Risk scenarios with the mean year as the likelihood metric.

Note that due to the data clumping observed in Figure 57 for Maximum year vs. Low TRL, the TOPSIS analysis for that combination does not result in a unique ranking for the portfolios. Portfolio 3 and Portfolio 12 were both identified as the best option. In total, Portfolio 3 was identified by seven of the nine readiness risk combinations as the best portfolio with respect to low readiness risk and Portfolio 12 was identified by three. Therefore, they are the top two portfolios with respect to low readiness risk.

The final step of the decision making process is to assess the ability to communicate performance risk and readiness risk of each combination. In Chapter Four, four different trade-off scenarios for technology portfolio down-selection were established. The measures used to communicate performance and readiness risk should be able to facilitate down-selection under any of these trade-off scenarios. The first scenario prioritizes technology portfolios that can provide an incremental performance improvement but have a low readiness risk. For performance risk, it may difficulty to determine incremental performance through the use of S/N along because the absolute values of S/N provide no relevant information. However, S/N paired with WPV or TCE does provide information on the expected performance. A technology portfolio with a WPV above or near the goal or a TCE close to the goal would imply potential to provide incremental performance improvement. In contrast, POS provides a lot of performance information by itself and even more when it is paired with WVP or TCE. Technology portfolios that have a high POS are indicative of an incremental performance improvement. This is validated further when the WVP or TCE is high. For readiness risk, low readiness risk can be identified through any of the provided depictions.

The second scenario prioritizes technology portfolios that have the potential to provide large improvements in performance. Again, it is difficult to determine the exact expected performance through the use of S/N. While a high S/N could be indicative of a good expected performance, it could also be driven by a low amount of uncertainty. Therefore, the information provided by TCE or WPV would be very important to differentiate which aspect is driving the S/N. As for POS, a high POS is clearly indicative of good expected performance. Furthermore, portfolios that have a 100% POS and the best overall performance can be distinguished through the use of WPV.

The third scenario prioritizes technology portfolios that have low to moderate readiness risk and performance risk. Therefore, any combinations for readiness risk and performance risk that create a spread in the data and enable comparisons could be used for this scenario. The final scenario prioritizes technology portfolios that have low performance risk. Since performance risk is not included, it does not matter which combination is used. For readiness risk, any combination that provides a spread is the data is sufficient.

5.2.2.4 Selection of Additional Technologies

The final portion of *Technology Portfolio Evaluation and Selection* addresses the selection of additional technologies to supplement a down-selected technology portfolio. It was established that after a technology portfolio is down-selected, decision makers may desire to select additional technologies based on their individual characteristics. These technologies would be selected to backup technologies included in the selected portfolio that have a high individual readiness or performance risk.

Readiness risk of an individual technology is comprised of its current TRL and the number of years until it reaches TRL 9. Both of these measures are readily available so the identification of a technology with high readiness risk is trivial. Therefore, the focus of this assessment is to determine how a single technology in a portfolio affects the performance risk and identify candidate technologies to back it up.

In Hypothesis 2.4 it was proposed that the identification of how technologies affect the POS of a technology portfolio would provide the information required to prioritize individual technologies. Therefore, a process was formulated to obtain this information. It was observed that the characteristics of this problem were similar to the problem addressed through the OAT experiments of the previous phase. In both instances, the objective is to determine the sensitivity of a metric with respect to a single technology. Therefore, an OAT approach was pursued.

Recall, in the previous OAT approach the control scenario was all non-baseline technologies turned off. Each experiment then turned on technologies one at a time and see how they affected the vehicle performance. In the context of this problem, it is more relevant for the control scenario to have all of the technologies in the portfolio of interest on. Each experiment would then turn a single technology off and compare the new probabilistic vehicle performance with original performance of the portfolio. To differentiate this new process from the original OAT approach, it will be referred to as the portfolio-specific OAT, or P-OAT.

This P-OAT process was implemented for the previously defined Portfolio 2. Portfolio 2 contains eight non-baseline technologies, so there are eight P-OAT experiments that contain seven non-baseline technologies each. Triangular distributions were used to represent the technology uncertainty and it was propagated using 50,000 case Monte Carlo analyses with the ANNs. The effect a technology has on an objective's POS was calculated by subtracting the POS of the P-OAT experiment where that technology was excluded from the original results. If the resulting delta is a positive value, then that technology has a positive effect on the POS. Likewise, a negative delta corresponds to a negative contribution to the POS.

After each P-OAT experiment was conducted the results were summarized and visualized. The POS deltas were plotted to form what is referred to as waterfall charts for each objective metric. The POS waterfalls are presented in Figure 76. The technologies are color-coded by their technology category, which allows a visual identification of which categories are driving the performance.

The P-OAT results in Figure 76 provide interesting information. First, it is noted that the POS for fuel burn reduction is heavily driven by one of the airframe aerodynamic technologies, T69.1. The other technologies either have no effect or a negative effect on the fuel burn reduction POS. For NOx emissions POS is driven by a single technology, T22.1. While none of the other seven technologies positively effect the POS, they also do not negatively impact it. Lastly, the noise margin results are greatly skewed by the large negative impact of T22.1. Although it is not noticeable, the noise technologies have a positive impact on the POS.

It was identified that T22.1 is the only technology driving the NOx performance. Therefore, if it does not achieve the appropriate readiness or its performance degrades during the development process, the NOx goal would likely not be met. This results in the conclusion that T22.1 would be prioritized first for being backed up by another candidate technology.

5.2.2.5 Technology Portfolio Evaluation and Selection Observations

The processes followed to calculate the measures used for performance and readiness risk were clearly outlined and the results of each different risk depiction were discussed. Hypothesis 2.2 stated that a readiness risk depiction that includes a readiness measure and difficulty measure representative of the entire portfolio would be sufficient to make technology down-selection trades. When only the readiness risk was calculated using the Max Year vs. Low TRL scenario, it was representative of a single technology in the portfolio. These measures were considered in the analysis to test whether the technology with the highest readiness risk was representative of the readiness risk of the entire portfolio. It is concluded from the TOPSIS results and the results shown in Figure 57 that this is not true because these results do not match the portfolio rankings from the aggregate measures.

The results provided by the aggregate measures do, however, provide a spread in the data the enables the identification of technology portfolios with both high and low readiness risk. Therefore, it is determined that Hypothesis 2.2 is supported. Furthermore, it is determined that any of the four combinations for readiness risk from the aggregate measures are suitable for a readiness risk assessment that aids technology down-selection.

Hypothesis 2.3 stated that a performance risk depiction that provides a measure of how far from the objectives a portfolio could end up and the POS would be sufficient for technology down-selection. S/N and POS were both assessed for their ability to communicate expected performance. Based on the observations previously made, it is concluded that S/N is a better metric to use when you need to differentiate portfolios that are clumped together with similar POS values. However, if portfolios do not have similar POS values and a comparison of performance is required, POS is a better measure to use. As for TCE versus WPV, it was observed that both provide similar trends and rankings among the portfolios. However, TCE does not provide relevant information for portfolios that have a 100% POS because there is no tail to evaluate. Therefore, WPV is recommended for the consequence measure in performance risk assessments. Based upon these observations, it was determined that Hypothesis 2.3 is partially supported, and should be augmented to include S/N when the portfolios under consideration have similar POS values to create a greater spread in the data.

Finally, it was observed that the results provided by the POS contribution waterfall charts enable the prioritization of technologies based upon their impact on the performance of the technology portfolio. Furthermore, it was demonstrated that the outlined P-OAT process will result in the information required to form the POS waterfall charts. These observations therefore support Hypothesis 2.4.

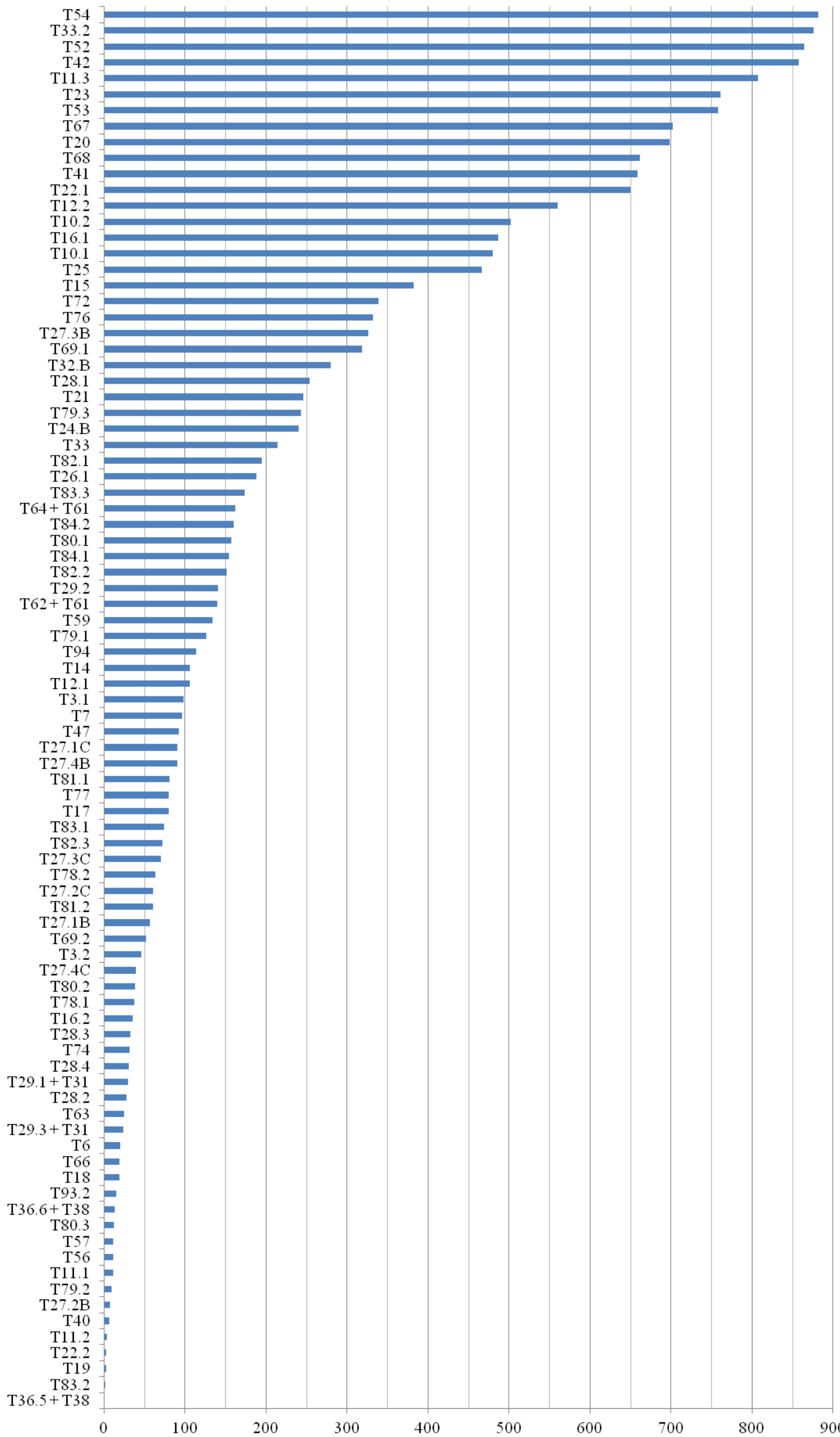

Figure 54: Count of technologies in MOGA non-dominated results.

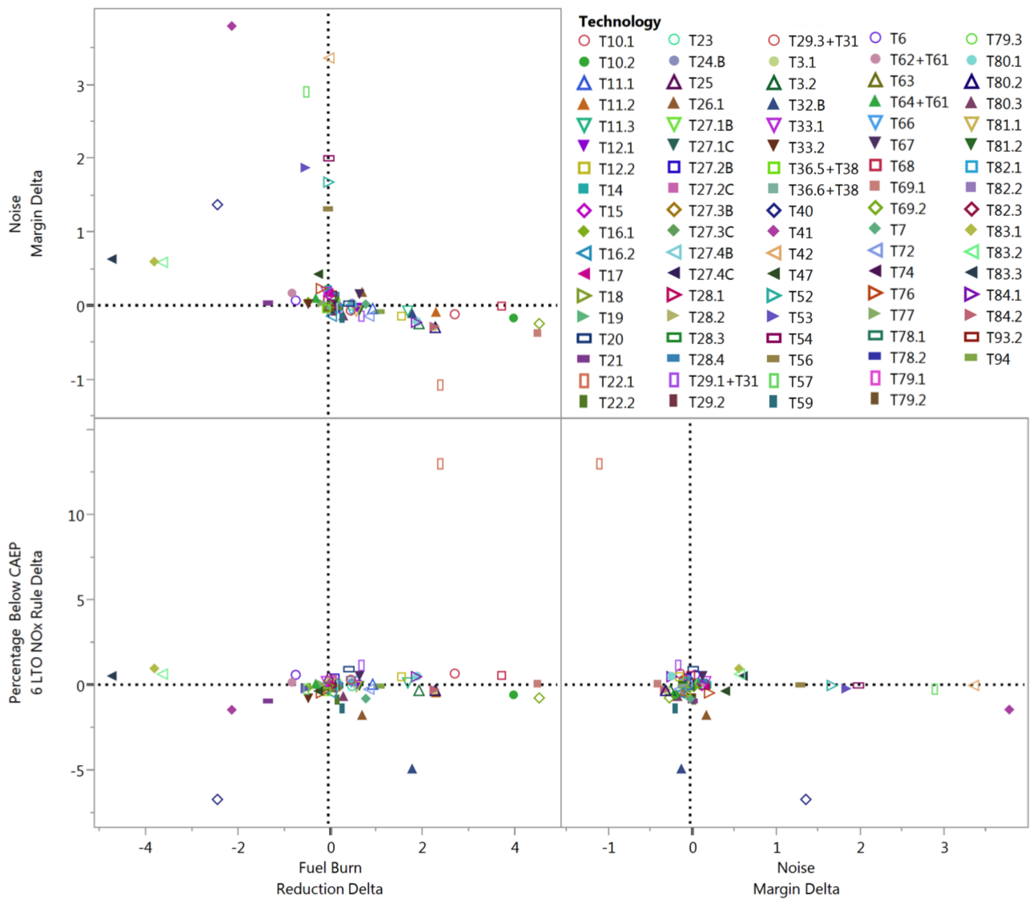

Figure 55: Sensitivity of performance objective metrics to individual technologies.

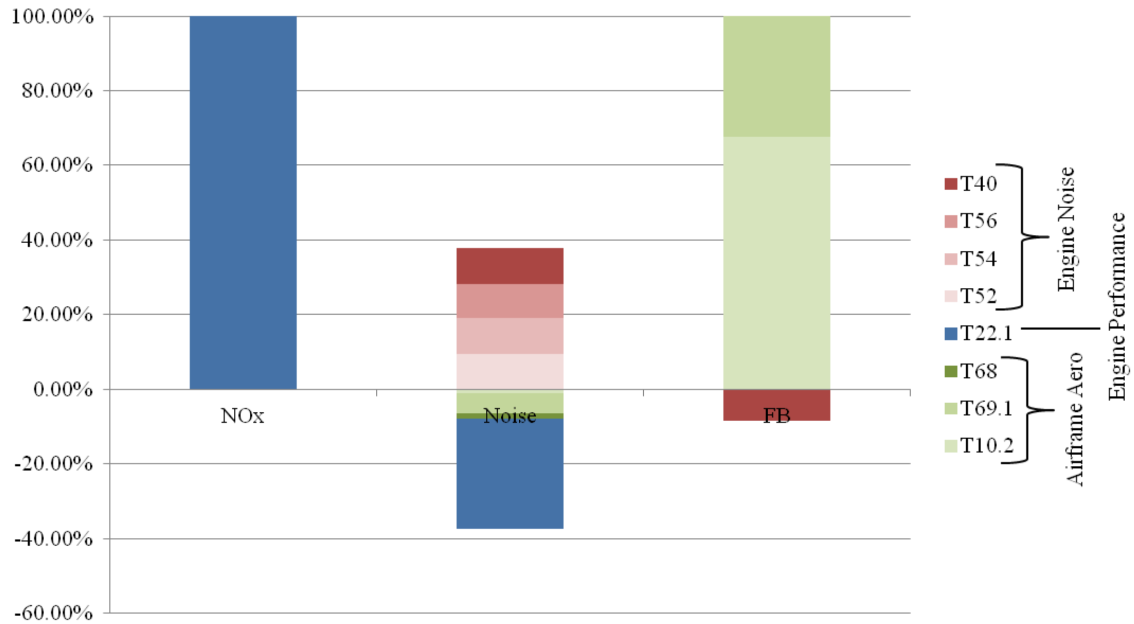

Figure 76: Contribution of each technology in the selected portfolio to the POS for NOx emissions, noise margin, and fuel burn reduction.

CHAPTER VI

INVESTIGATION OF EXPERIMENT PLANNING AND RISK PROGRESSION

6.1 Examination of Phase 3

A set of experiments was conducted to test Hypotheses 3.0-3.3. The first experiment in the set addresses Hypothesis 3.0. It involves formulating the proposed morphological analysis to assess technology readiness and demonstrating it on a new material technology currently in development. The second experiment utilizes a technology portfolio from Experiment Set 2 to implement the proposed experimentation design process and addresses Hypotheses 3.1-3.3.

6.1.1 Readiness Assessment Process

Hypothesis 3.0 proposed the use of morphological analysis to aid the measurement and communication of readiness. The morphological analysis was formulated and is outlined in the proceeding subsection.

6.1.1.1 Finalization of Morphological Analysis

Recall, Figure 29 displayed the identified attributes of readiness. The next step in formulating the morphological analysis was to consult the literature again to identify a set of options for each attribute. The various TRL definitions found in the literature were consulted along with the work done by Jimenez and Mavris[46]. The results of this research are shown in Figure 77. The options identified for each attribute will now be further explained.

Attribute	Attribute options			
Type of test environment	Computer Simulated	Lab	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	Simplified, some assumptions	Controlled	Operational
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	Actual hardware
Scale of test article	Sub-scale	Full-scale		
Level of test article	Single technology	Single sub-system, multiple technologies	Multiple sub-systems	Full system

Figure 77: Final morphological analysis for technology readiness.

The first two attributes address the test environment. The test environment attributes are the type of test environment and the fidelity of the test environment. In this context, fidelity is a measure of realism. There are three identified potential options for the type of test environment: computer simulated, lab, or real-world. Computer simulated would be any analytical environment utilized for analysis. Examples include computational fluid dynamics (CFD) environments or finite element modeling (FEM) environments. Computer simulated environments are used throughout development; however, very early phases of development may utilize only computer environments.

Lab environments are any controlled, non-computer simulated environment. Examples of such are wind tunnels and other indoor testing facilities. Lab environments are utilized during early and mid stages of technology development. Lastly, real-world environments are exactly as they seem. They are the actual operating environment that the technology or system is intended to perform in. For an aircraft system this would be the outdoor environment, or the Earth's atmosphere. Real-world environments are utilized during the late stages of development for system validation and certification.

The fidelity of the test environment is divided into four different options: simplified with a large number of assumptions, simplified with few assumptions, controlled, and operational. The simplified options occur when only certain aspects of an environment are considered and other aspects are assumed constant or non-existent. In these environments simplifying assumptions are utilized to either isolate a condition or phenomenon. An issue that may arise is the separation between the two options. It may seem like the end of the first option and the beginning of the next is not well defined. However, both were included because, depending on the technology and its defining physics, more than one simplified option may be desired. These options would be utilized during the early and mid stages of development.

The controlled option is any environment where few or no simplifications are made but some aspects of the environment may be under control. The aspects under control would be parts of the environment that are not in control of the aircraft operator during operation. An example of this is when a flight test is conducted in the atmosphere, but experimenters ensure the weather will be clear, warm, and calm. This option would be utilized during mid to late stages of development. The last option, operational, is self-explanatory. It is the environment the entity is designed to operate in without attempting to control anything. This option is utilized during the late stages of development when a system is undergoing validation and certification.

The final three attributes define the test article. The first attribute is the fidelity of the test article and it is divided into four options: a non-physical model, a prototype with non-working parts, a prototype with working types, and actual hardware. A non-physical model is a representation of the technology or system in a computer simulated environment. An example is an airfoil model analyzed in a CFD environment. Non-physical models are utilized in early stages of development to explore the design space and test ideas. Additionally, they are utilized throughout technology development for pre-test predictions.

The next two options are physical models. A prototype with non-working parts is one where simplifications have been made and only certain aspects of the model are realistic. A prototype with working parts is one where few to no simplifications are made, and the test article is very realistic but still not a final representation. Similarly to the test environment relevance, it may seem difficult to determine the separation between these two options. Two options are enumerated here instead of a single prototype options because it is recognized that there may be varying levels of prototypes. Additionally, it is recognized that a technology or system may require more than two prototype levels to fully enumerate all of the options. It is expected that the prototype without working parts would be utilized during early to mid stages of development and the prototype with working parts would be utilized during mid to late stages of development. The final option, actual hardware, refers to test articles that are no longer models but exact representations of the technology or system.

The scale of the test article is simply divided into two options: sub-scale and full scale. Sub-scale is any size that is not the anticipated size of the final article. Throughout most of development the test articles will be sub-scale, until the final phases. It is acknowledged that there are an infinite number of scales that can be defined as sub-scale. If a technology development program wishes to divide sub-scale into multiple options or specific sizes, the morphological analysis can be altered.

The final attribute is the level of the test article. In this context, level refers to the level of the system that is being modeled. Level can also be referred to as the number of integrated parts being modeled. This attribute is divided into four options: a single technology, a single sub-system with multiple technologies, multiple sub-systems, and the full system. As development progresses, technologists should begin integrating the technology or components under development with supporting elements and other sub-systems of the system until the fully integrated system is represented. Therefore, the first option is representative of early phases of development, the second option is utilized during mid phases of development, the third option is utilized during mid to late phases of development, and the final option is utilized during the final phases of development.

After the definition of the attribute options, the morphological analysis is used to represent each TRL level based upon the definitions presented in Chapter Two. The resulting TRL depictions are shown in Figure 78. The options highlighted in blue for each attribute define the characteristics of the given TRL level. Notice some TRL levels have multiple options highlighted for a single attribute. This is a result of interpretation of the definitions. It is felt that some could be either option, and it will ultimately depend on how the morphological analysis is created for the technology in question.

In general, it is observed that the selected options for each attribute move towards the right as the TRL increases. TRL 1 is defined by the far left options for each attribute, which is representative of the lowest fidelity analysis. TRL 9 is defined by the far right options for each attribute, which corresponds to the highest fidelity analysis.

6.1.1.2 Implementation of Morphological Analysis

The morphological analysis was tested by implementing it on a structural technology currently under development by The Boeing Company and NASA. The technology is called Pultruded Rod Stitched Efficient Unitized Structure, or PRSEUS.[111] PRSEUS is being developed specifically for the centerbody, or fueslage-like area, of the hybrid wing body (HWB) vehicle concept. It aims to address both structural and manufacturing challenges that face the HWB design.

The HWB concept has the potential to provide a lighter aircraft with increased performance and a smaller noise footprint. However, the configuration faces a challenge in creating a non-circular pressure cabin that is lightweight as well as economical

TRL 1

Attribute	Attribute options			
Type of test environment	**Computer Simulated**	**Lab**	Real-world	
Fidelity of test environment	**Simplified, large amount of assumptions**	Simplified, some assumptions	Controlled	Operational
Fidelity of test article	**Non-physical**	**Prototype, non-working parts**	Prototype, working parts	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	**Single technology**	Single sub-system, multiple technologies	Multiple sub-systems	Full system

TRL 2

Attribute	Attribute options			
Type of test environment	**Computer Simulated**	**Lab**	Real-world	
Fidelity of test environment	**Simplified, large amount of assumptions**	Simplified, some assumptions	Controlled	Operational
Fidelity of test article	**Non-physical**	**Prototype, non-working parts**	Prototype, working parts	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	**Single technology**	Single sub-system, multiple technologies	Multiple sub-systems	Full system

TRL 3

Attribute	Attribute options			
Type of test environment	Computer Simulated	**Lab**	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	**Simplified, some assumptions**	Controlled	Operational
Fidelity of test article	Non-physical	**Prototype, non-working parts**	Prototype, working parts	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	**Single technology**	Single sub-system, multiple technologies	Multiple sub-systems	Full system

TRL 4

Attribute	Attribute options			
Type of test environment	Computer Simulated	**Lab**	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	**Simplified, some assumptions**	**Controlled**	Operational
Fidelity of test article	Non-physical	**Prototype, non-working parts**	**Prototype, working parts**	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	**Single technology**	Single sub-system, multiple technologies	Multiple sub-systems	Full system

TRL 5

Attribute	Attribute options			
Type of test environment	Computer Simulated	**Lab**	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	**Simplified, some assumptions**	**Controlled**	Operational
Fidelity of test article	Non-physical	**Prototype, non-working parts**	**Prototype, working parts**	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	**Single technology**	**Single sub-system, multiple technologies**	Multiple sub-systems	Full system

TRL 6

Attribute	Attribute options			
Type of test environment	Computer Simulated	**Lab**	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	**Simplified, some assumptions**	**Controlled**	Operational
Fidelity of test article	Non-physical	**Prototype, non-working parts**	**Prototype, working parts**	Actual hardware
Scale of test article	**Sub-scale**	Full-scale		
Level of test article	Single technology	**Single sub-system, multiple technologies**	**Multiple sub-systems**	Full system

TRL 7

Attribute	Attribute options			
Type of test environment	Computer Simulated	**Lab**	Real-world	
Fidelity of test environment	Simplified, large amount of assumptions	Simplified, some assumptions	**Controlled**	Operational
Fidelity of test article	Non-physical	Prototype, non-working parts	**Prototype, working parts**	Actual hardware
Scale of test article	Sub-scale	**Full-scale**		
Level of test article	Single technology	Single sub-system, multiple technologies	**Multiple sub-systems**	**Full system**

TRL 8

Attribute	Attribute options			
Type of test environment	Computer Simulated	Lab	**Real-world**	
Fidelity of test environment	Simplified, large amount of assumptions	Simplified, some assumptions	Controlled	**Operational**
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	**Actual hardware**
Scale of test article	Sub-scale	**Full-scale**		
Level of test article	Single technology	Single sub-system, multiple technologies	Multiple sub-systems	**Full system**

TRL 9

Attribute	Attribute options			
Type of test environment	Computer Simulated	Lab	**Real-world**	
Fidelity of test environment	Simplified, large amount of assumptions	Simplified, some assumptions	Controlled	**Operational**
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	**Actual hardware**
Scale of test article	Sub-scale	**Full-scale**		
Level of test article	Single technology	Single sub-system, multiple technologies	Multiple sub-systems	**Full system**

Figure 78: Definition of TRL scale using morphological analysis.

to produce. Additionally, the HWB concept faces a unique bi-axial loading pattern that occurs during maneuver loads. Therefore, it requires the design of an improved fuselage panel that is bidirectionally stiffened to ensure the wing bending loads are handled by the frame and the fuselage bending loads are handled by the stringers.

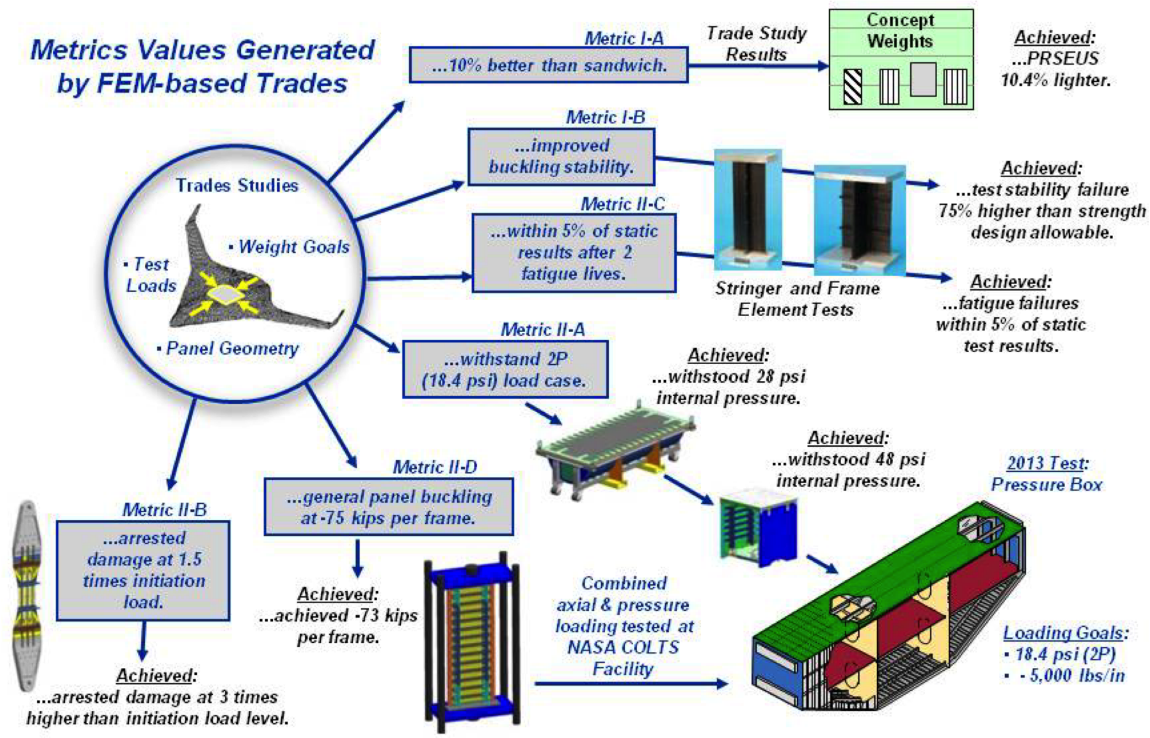

Figure 79: Summary of PRSEUS test plan from initial anlysis to multi-bay box experimentation. (Reproduced from [111])

Current state-of-the-art materials cannot overcome these challenges, so a new composite material was required. This led to the development of PRSEUS. PRSEUS enables a one piece panel design that has seamless transitions and damage-arrested interfaces. It provides unprecedented levels of fiber tailoring and the potential for structural optimization.

As mentioned, PRSEUS is being developed by Boeing with assistance from NASA. It is currently one of eight technologies selected for further development during Phase 2 of the NASA ERA program. A series of experiments performed in the past and planned for the future have been well-defined and published. The PRSEUS test plan is shown in Figure 79. A summary of each experiment is now presented to identify relevant options for the attributes of the morphological analysis.

Single-stringer compression panel:

A single-stringer panel was tested under compression loading conditions.

The purpose of the experiment was to characterize the buckling stability for the stringer components and assess the damage arrestment of the stitching after the loading is applied. Two test specimens were created and both were tested statically to failure. The specimen was held in place using an aligning device to restrict rotation and movement. Side restraints were utilized to inhibit buckling along the panel edges. The following metrics were were measured during the experiment: slope of the load versus the deflection, the failure loads and strains, the buckling load-to-failure load ratio, and the weight of the element.

Single-frame compression panel:

A single-frame panel was tested under compression loading conditions. The purpose of the experiment was to characterize the buckling stability for the frame components and assess the damage arrestment of the stitching after the loading is applied. Two test specimens were created that consisted of a single frame with two stringers. Both test specimen were tested statically to failure. The specimen were held in place using an aligning device to restrict rotation and movement. Side restraints were utilized to inhibit buckling along the panel edges. The load was balanced on the specimen within $\pm 10\%$ by utilizing a set of strain gauges. The following metrics were were tracked during the experiment: the out-of-plane deflection, slope of the load versus deflection, the failure loads, and the weight of the element.

Single-frame panel fatigue cycling:

A single-frame panel was tested through fatigue cycling. The purpose of the experiment was to characterize the fatigue performance and assess the damage arrestment of the stitching under fatigue. The test consisted of axial compression tests of 55,000 cycles without removing the load between cycles. Metal side restraints were added to suppress out-of-plane motion at unloaded edges. Paint was added to the outer moldline of the specimen to aid motion tracking. The following metrics were were tracked during the experiment: slope of the load versus deflection pre-fatigue versus post-fatigue ratio, the fatigue buckling load versus pristine buckling load ratio, load versus strain slope pre-fatigue versus post-fatigue ratio, and the weight of the element.

Pressure Box:

A pressure box was tested through multiple loading conditions. The purpose of the experiment was to confirm the PRSEUS panels will contain the design load internal pressure and isolate the secondary bending effects. The experiment established the overall structural viability of the PRSEUS design. The test specimen was a 108 inch by 48 inch panel with two 20 inch frame spacing and 15 6 inch stringer spacing. Aluminum doublers on the outer moldline were used to connect the panel to the pressure chamber to enable transfer of the bending load to the internal stiffeners. Internal fittings connected the frames to the pressure chamber to enable bending continuity. Pre-test predictions were conducted through finite element modeling. The following metrics were were tracked during the experiment: predicted failure load, location, strain, and stresses; panel displacement, strains, and failure load; and the weight of the panel.

Chordwise tension panel:

A panel was tested for chordwise tension. The purpose of the experiment was to demonstrate damage-arrest design advantages and validated the

HWB minimum-gauge fuselage geometry. Two test specimen were created and they were dog-bone shaped tension panels that were comprised of three axial stringers and two frames perpendicular to the load. The primary fiber direction was parallel to the frames. During the experiment, the panel was statically loaded to failure, with pauses for assessment of local failures. The following metrics were were tracked during the experiment: displacement between center frames at each stringer, pin-to-pin displacement of specimen, skin out of plane displacement, load versus deflection slope, failures loads and modes, and the panel weight.

Spanwise compression panel:

A panel was tested for spanwise compression. The purpose of the experiment was to assess the buckling stability of the PRSEUS integral frame feature. The test specimen consisted of two frames and sixteen stringers with side restraints to inhibit local buckling. Preliminary FEM analysis was conducted to determine the critical compressive load. The specimen was statically loaded to failure. The following metrics were were tracked during the experiment: the predicted buckling loads and strains, the stability versus strength, the buckling failure loads, and the panel weight.

Pressure Cube:

A pressure cube was tested for the purpose of demonstrating the feasibility of containing pressure with all PRSEUS panels, verifying the panels would hold the load cases, and development of appropriate fittings for PRSEUS joints. The test specimen was a crown panel representative of an upper skin pressure panel. The floor panel is not exactly representative of the HWB floor, but it utilizes the same stringer pitch. The following metrics were tracked during the experiment: the pristine strains, the deflections at the design load, and the pressure cube weight.

Multi-Bay Box:

A large scale PRSEUS model is being for the purpose of demonstrating PRESUS' performance under combined loading conditions of a realistic operational environment. The test specimen is a 30 foot long multi-bay box(MBB) that consists of eleven total PRSEUS panels. Pre-test FEM analysis was performed to predict the deflections, stresses, strains, and failures. The following metrics will be tracked during the experiment: the displacements, strains, strains versus combined loading conditions, and the weight of the MBB.

Details of the described experimentation outlines the progression of the level of the test article and the fidelity of the testing environment. For the test article level, it begins with coupon testing and progresses to the MBB. However, the MBB is not the final test article level for PRESUS; in the future, experimentation will continue until a full-scale HWB with a PRSEUS centerbody is tested.

In the context of PRSEUS, the fidelity of the test environment can be represented by the type of loading scenario applied to the model. The loading scenarios progressed from a single load type in isolation to the realistic load scenario planned for the MBB test. The only option missing would be the actual flight loads from a flight test.

The PRESUS observations were summarized and formalized through the creation of the PRSEUS-specific morphological analysis. Figure 80 displays the morphological analysis. Note the attributes other than the environment fidelity and test article level have remained the same and do not require other options to adequately characterize the PRSEUS technology.

Attribute	Attribute options					
Type of test environment	Computer Simulated	Lab	Real-world			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	Multiple load scenarios	Realistic loading		
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	Actual hardware		
Scale of test article	Sub-scale	Full-scale				
Level of test article	Coupon	Single stringer/single frame	Panel	Box, multiple panels	HWB Centerbody	Entire HWB system

Figure 80: Morphological analysis formulation for PRSEUS technology.

Next, the PRSEUS-specific morphological analysis was utilized to characterize each level of the TRL scale. The baseline TRL definitions from Figure 78 were utilized and mapped to the PRSUES-specific morphological matrix shown in Figure 80. The results of this mapping are shown in Figure 81. The options highlighted in blue for each attribute define the type of experimentation that should have been previously completed for the PRSEUS technology to be considered the corresponding TRL. The progression of the options selected for each attribute is clearly left to right as the TRL increases.

Once the technology-specific TRL definitions have been created though morphological analysis, it is easy to observe how they could be used to either define required experimentation or measure the TRL achieved by past experimentation. It is acknowledged that the attribute options for PRSEUS were determined by consulting the actual experimental plan, whereas in an actual implementation of this process the technology specific morphological matrix should be made prior to performing experimentation.

TRL 1

Attribute	Attribute options					
Type of test environment	**Computer Simulated**	**Lab**	Real-world			
Fidelity of test environment	**Singular load type in isolation**	Singular load type, fatigue	Multiple load scenarios	Realistic loading		
Fidelity of test article	**Non-physical**	**Prototype, non-working parts**	Prototype, working parts	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	**Coupon**	Single stringer/ single frame	Single Panel	Box, multiple panels	HWB Centerbody	Entire HWB system

TRL 2

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	**Singular load type in isolation**	Singular load type, fatigue	Multiple load scenarios	Realistic loading		
Fidelity of test article	Non-physical	**Prototype, non-working parts**	Prototype, working parts	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	**Coupon**	Single stringer/ single frame	Single Panel	Box, multiple panels	HWB Centerbody	Entire HWB system

TRL 3

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	**Singular load type in isolation**	**Singular load type, fatigue**	Multiple load scenarios	Realistic loading		
Fidelity of test article	Non-physical	**Prototype, non-working parts**	Prototype, working parts	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	Coupon	**Single stringer/ single frame**	Single Panel	Box, multiple panels	HWB Centerbody	Entire HWB system

TRL 4

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	**Singular load type in isolation**	**Singular load type, fatigue**	Multiple load scenarios	Realistic loading		
Fidelity of test article	Non-physical	**Prototype, non-working parts**	Prototype, working parts	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	Coupon	Single stringer/ single frame	**Single Panel**	Box, multiple panels	HWB Centerbody	Entire HWB system

TRL 5

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	**Multiple load scenarios**	Realistic loading		
Fidelity of test article	Non-physical	**Prototype, non-working parts**	**Prototype, working parts**	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	Coupon	Single stringer/ single frame	**Single Panel**	Box, multiple panels	HWB Centerbody	Entire HWB system

TRL 6

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	**Multiple load scenarios**	Realistic loading		
Fidelity of test article	Non-physical	Prototype, non-working parts	**Prototype, working parts**	Actual hardware		
Scale of test article	**Sub-scale**	Full-scale				
Level of test article	Coupon	Single stringer/ single frame	Single Panel	**Box, multiple panels**	HWB Centerbody	Entire HWB system

TRL 7

Attribute	Attribute options					
Type of test environment	Computer Simulated	**Lab**	Real-world			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	**Multiple load scenarios**	Realistic loading		
Fidelity of test article	Non-physical	Prototype, non-working parts	**Prototype, working parts**	Actual hardware		
Scale of test article	Sub-scale	**Full-scale**				
Level of test article	Coupon	Single stringer/ single frame	Single Panel	Box, multiple panels	**HWB Centerbody**	Entire HWB system

TRL 8

Attribute	Attribute options					
Type of test environment	Computer Simulated	Lab	**Real-world**			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	Multiple load scenarios	**Realistic loading**		
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	**Actual hardware**		
Scale of test article	Sub-scale	**Full-scale**				
Level of test article	Coupon	Single stringer/ single frame	Single Panel	Box, multiple panels	HWB Centerbody	**Entire HWB system**

TRL 9

Attribute	Attribute options					
Type of test environment	Computer Simulated	Lab	**Real-world**			
Fidelity of test environment	Singular load type in isolation	Singular load type, fatigue	Multiple load scenarios	**Realistic loading**		
Fidelity of test article	Non-physical	Prototype, non-working parts	Prototype, working parts	**Actual hardware**		
Scale of test article	Sub-scale	**Full-scale**				
Level of test article	Coupon	Single stringer/ single frame	Single Panel	Box, multiple panels	HWB Centerbody	**Entire HWB system**

Figure 81: TRL descriptions for the PRSEUS technology using the morphological analysis.

6.1.1.3 Observations and Discussion

The morphological analysis for readiness assessment was formulated and its capabilities were demonstrated through the implementation on the PRSEUS technology. The results demonstrated that the morphological analysis is flexible and the different attribute options can be tailored to any technology under consideration. Furthermore, it is observed that the ability to assign TRL requirements and then communicate the characteristics of a TRL has been improved.

Hypothesis 3.0 stated that the readiness measurement process created by the morphological analysis would be traceable and complete. Based upon the method formulation, implementation results, and corresponding observations, it is determined that this hypothesis has been confirmed. The morphological analysis achieves both of these characteristics and provides a unique communicate tool.

6.1.2 Experiment Planning Process

The process for *Plan Experimentation* is provided in Figure 82. This process involves first prioritizing technologies for experimentation based upon their current readiness risk and performance risk, and then utilizing information from readiness assessments and uncertainty analysis to recommend future experimental plans. The remainder of Experiment Set 3 provided in the proceeding sub-sections will address Hypotheses 3.1-3.3 and discussed on how the results led to the formulation of this final process is provided.

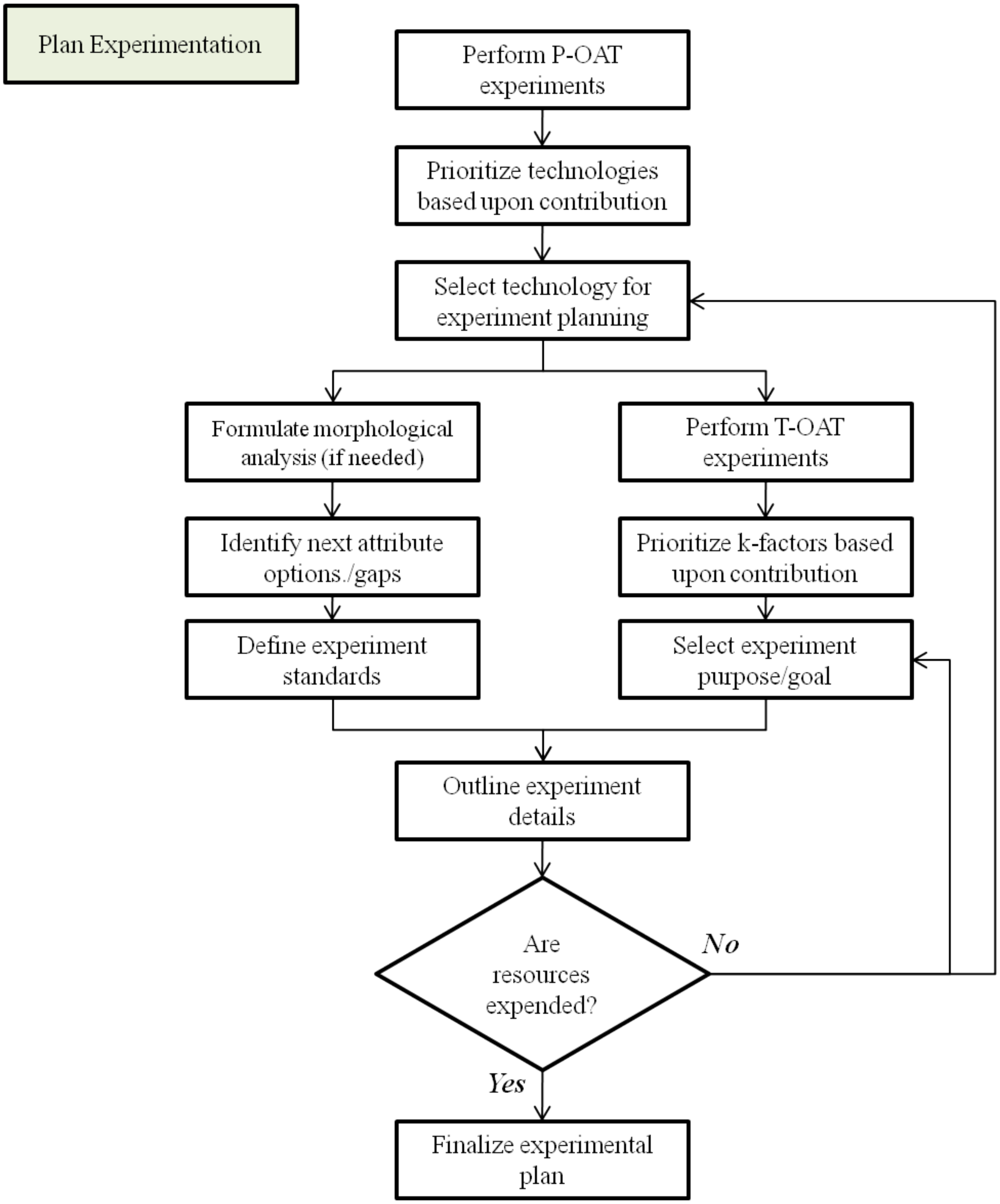

Figure 82: Process flowchart for experiment planning.

6.1.2.1 Technology Prioritization for Experimentation

The first step of planning experimentation is prioritizing the technologies. Several different trade-off scenarios were presented for the selection, or prioritization, of technologies for further experimentation. The trade-off scenarios led to Hypotheses 3.1 and 3.2, which proposed different measures for performance risk and readiness risk, respectively.

In the context of this development phase, technologies are individually compared to one another and aggregate characteristics of the entire portfolio are not required. For readiness, the comparison of technologies to each other is quite simple. The raw values for current TRL and years to TRL 9 can be used to represent readiness consequence and likelihood, respectively. However, for performance more analysis is required.

For performance risk, it was hypothesized that a measure that captures the amount of uncertainty associated with a technology and its impact on POS could be used to communicate performance risk. A few concerns arose with respect to the amount of uncertainty associated with a single technology. First, the level of the system used to quantify the amount of uncertainty that surrounds a technology can greatly change the outcome of the assessment. When it is desired to track uncertainty at the technology or component level where the technology impacts are defined, it is unclear which technology impact should be used. Technologies can be mapped to several impacts, as previously demonstrated, and each impact can have a different amount of uncertainty surrounding it.

Furthermore, the different k-factors are not all equally defined. The combination rules for the k-factors depend on the nature of the analysis code and the phenomena under investigation. For example, some k-factors multiply with system metrics to realize the impact and others can completely replace the system metric it is mapped to. These combination rules effect how the k-factors are defined and how the uncertainty is realized, which could make comparisons of technology uncertainty at the impact level misleading.

Finally, using the resulting uncertainty surrounding a single system level objective due to a technology may not create a fair comparison among technologies. The effect a technology will have on an objective's uncertainty depends not only on the amount of uncertainty surrounding the technology's impacts, but also the relationship between the technology's discipline and the discipline of the objective. Therefore, the system level uncertainty may not be consistent for technologies with the same TRL. Based on these observations, the system level variance contributed by each technology for all three objectives will be used to provide comparisons.

In addition to the effect each technology has on the POS, the effect each has on the overall variance was also investigated. It is acknowledged that the process laid forth for the identification of additional technologies to supplement a previously selected technology portfolio is relevant. Therefore, the previously defined analysis procedure was revisited. It was demonstrated how the effect a single technology in a technology portfolio has on the POS of meeting a performance goal can be isolated through the use of the P-OAT analysis. Likewise, the results of the P-OAT experiments can also be used to show how the individual technologies affect the overall uncertainty, or variance, of a given metric.

The P-OAT process was repeated to assess the variance contribution of each technology. Portfolio 2, which was defined in the previous chapter through Table 23, was utilized again. The control scenario for this analysis was all eight non-baseline technologies of Portfolio 2 turned on and each P-OAT experiment involved turning one non-baseline technology off. The same triangular probability distributions were utilized to represent the technologies' performance uncertainty and the uncertainty was propagated using 50,000 case Monte Carlo analyses.

Once the probabilistic performance results for each experiment were obtained, the contribution to the overall variances for each of the three objective metrics was calculated. The contribution of a single technology was calculated for each objective metric by subtracting the variance from the P-OAT experiment where that technology is turned off from the control scenario variance. For a single objective metric, the calculated contributions of each technology were normalized by the sum of the contributions to obtain a percentage contribution. Normalization is required because the sum of the individual contributions will not equal the total variance observed in the control scenario due to unquantified interactions and sampling error.

Figure 83 displays the variance contribution results in a waterfall chart similar to the waterfall charts presented for POS in Figure 76. For Portfolio 2, it is observed that the airframe aerodynamic technologies as a whole contribute the most uncertainty to fuel burn reduction, the engine noise technologies contribute the most uncertainty to noise margin, and the engine noise and engine performance technologies drive the NOx emissions uncertainty. For specific technologies, T68 individually drives fuel burn reduction the most and T22.1 drives NOx emissions the most.

The results provided in Figure 76 and Figure 83 were next compared to each other to determine if they communicate similar or dissimilar information. For fuel burn reduction, the results are very similar and both enable the identification of the airframe aerodynamics technologies, T22.1, and T40 as driving the uncertainty. In contrast, the noise margin results show some agreements and a clear disagreement. It was discussed that T22.1 negatively drives the POS by a large margin, but does not appear in the variance contribution waterfall. However, the engine noise technologies provide contributions in both. Likewise, the results provided by both assessments for NOx emissions have some similarities and some dissimilarities. The results are similar because both identify T22.1 as the strongest uncertainty driver. However, the variance analysis identifies T40 as the second largest driver in uncertainty whereas the POS analysis shows it has minimal to no effect on the POS.

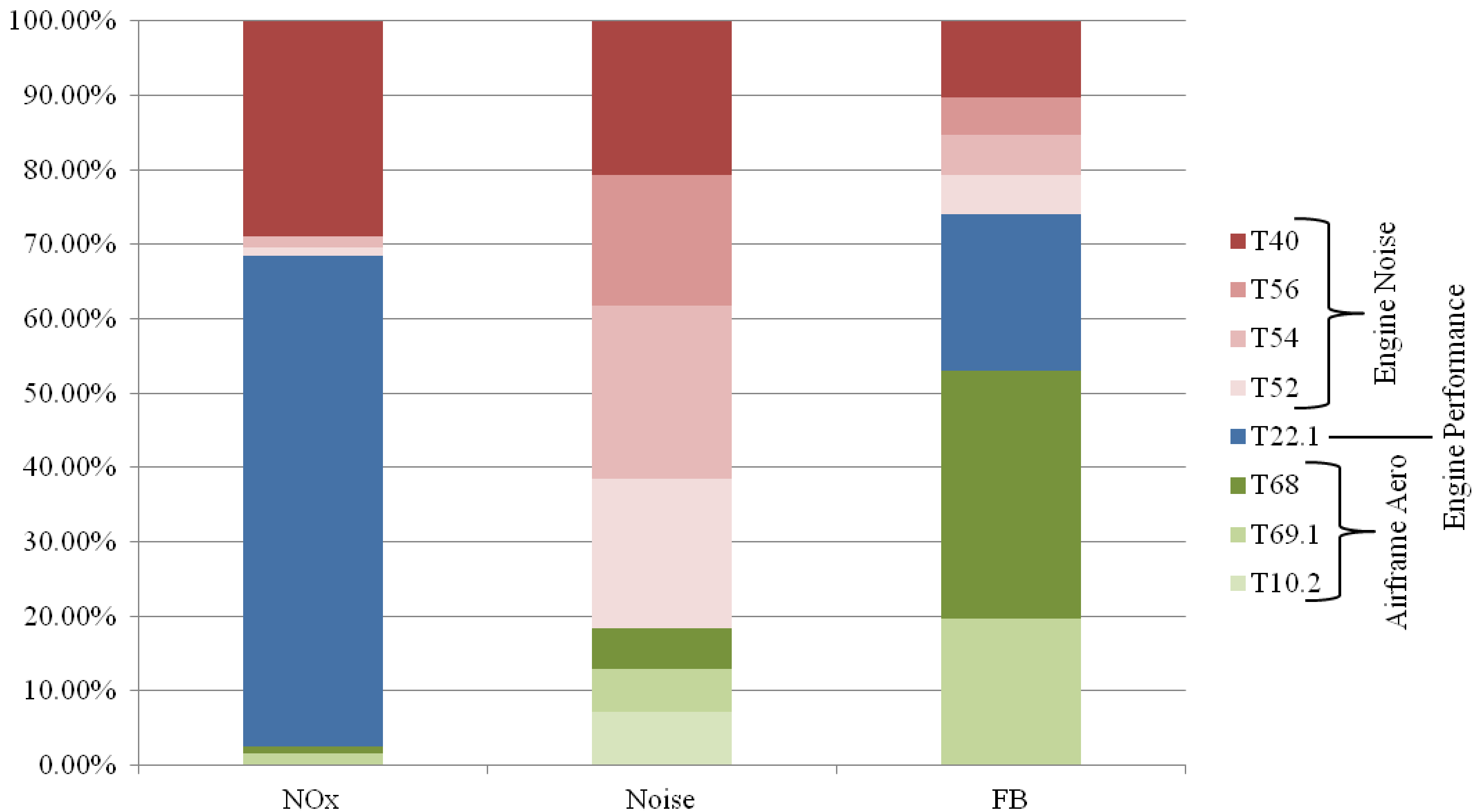

Figure 83: Contribution of each technology in the selected portfolio to the response variances.

The readiness and performance risk information for each technology in Portfolio 2 is summarized in Figure 84 and Figure 85. Next, the ability to make decisions based on the defined trade-off scenarios with this information was explored. The first trade-off scenario was to select the technology that contributes to the uncertainty in the performance the most. Figure 85 shows that T40 and T22.1 both have large variance contributions for two out of three of the of the performance metrics, but no single technology contributes the most for all three. Therefore, either T40 or T22.1 would be selected for this trade-off scenario. The second trade-off scenario was to select the technology that contributes to the POS of the goals the most. Again, Figure 85 shows there is no single technology that is drives all three POSs, but T22.1 is the sole driver of NOx emissions POS and T69.1 has a strong impact on the POS for both fuel burn reduction and noise margin. Therefore, either one of those technologies would be selected for this trade-off scenario.

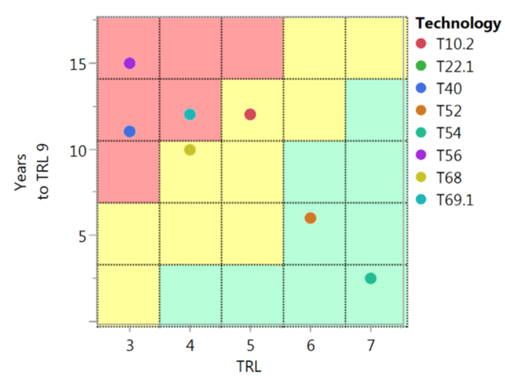

Figure 84: Readiness risk attributes of each technology in Portfolio 2.

The last two trade-off scenarios dealt with readiness risk. The first readiness trade-off scenario prioritizes technologies with the lowest current TRL in an effort to increase their TRL and decrease the portfolio's readiness risk. The second prioritizes technologies with the highest anticipated difficulty. As Figure 84 shows, T56 has both the lowest current TRL and the highest expected difficulty because it has an estimated 15 years until it will reach TRL 9. Therefore, T56 would be selected for experimentation under both of the final trade-off scenarios.

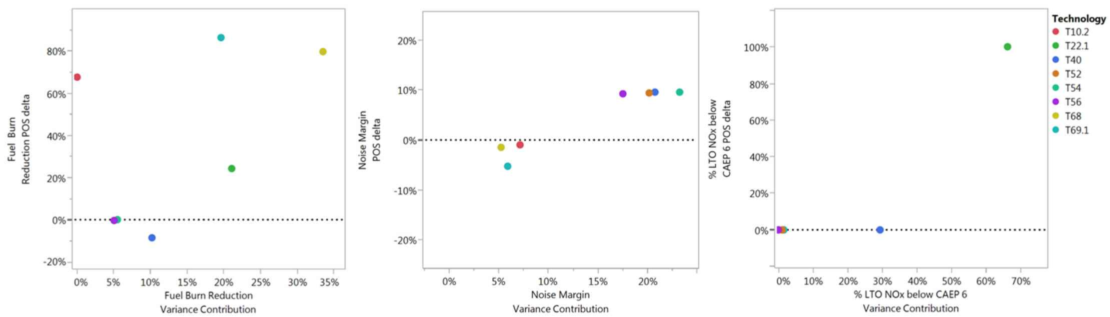

Figure 85: Performance risk attributes of each technology in Portfolio 2.

6.1.2.2 Experiment Design

After prioritization, experimentation for the selected technologies must be planned. The process proposed by Hypothesis 3.3 involves quantitative uncertainty analysis and the previously defined morphological analysis. The first step in implementation was to select a technology. From the prioritization results for Portfolio 2, T22.1 was selected. T22.1 is the compressor intercooler technology, which is an engine performance technology. Its impacts are mapped to five different technology k-factors: IntercoolerHX_ effect, LPCPR, IntercoolerBleedFlow, IntercoolerCoreDP, and IntercoolerNondimensionalWeight. Furthermore, T22.1 is currently considered to be at TRL 3 and will reach TRL 9 in 11 years.

It was proposed in Chapter Four that the experimentation planning process for a selected technology should not be affected by the trade-off scenario utilized to select the technology. Furthermore, it was stated that experiments should be planned to simultaneously increase readiness and decrease performance uncertainty. Figure 31 displays the proposed experiment design process.

The experiment design process for T22.1 began with defining the experiment standards. The results of the morphological analysis shown in Figure 78 were used to determine that a TRL 3 technology that is aiming to achieve TRL 4 must perform experimentation that meets the following standards: A sub-scale prototype of the technology itself, with working or non-working parts, should be tested in a simplified lab environment with few operational assumptions. In comparison to the standards for TRL 3, the past experimentation will need to be improved by increasing the fidelity of the test article and potentially the test environment.

The phenomena studied during the experimentation, or the type of measurements desired, is determined through uncertainty analysis. Similarly to the manner in which T22.1 was identified as a key uncertainty driver, its individual impacts were also prioritized through an OAT sensitivity analysis similar to the P-OAT process. In this context, the control scenario is all technologies in Portfolio 2 turned on, which is the same as it was for P-OAT experiments. Now, however, the experiments are defined by turning off the individual impacts of T22.1 one at a time and keeping all other impacts and the other technologies turned on. This enables identification of how the performance of the system is affected by the individual uncertain impacts of T22.1. This process will be referred to as the technology-specific OAT process, or T-OAT process.

The T-OAT process was implemented on T22.1 to demonstrate if and how it works. Five T-OAT experiments were defined, each with four of the technology impacts turned on and one turned off. Note that sometimes impacts must be on together or off together. In these situations they would be grouped into one impact and analyzed together. After defining the experiments, the technology uncertainty for each was characterized using triangular distributions. The distributions were propagated to the objective metrics through 50,000 case Monte Carlo analyses utilizing the previously defined ANNs. Th output statistics of the objective metrics were calculated for each T-OAT experiment and a comparison of the results to the results of the control scenario provided the effects of the impacts.

Figure 86 shows the results of the T-OAT analysis in the form of a waterfall chart for variance contribution. IntercoolerBleedFlow and LPCPR contribute the most to the overall variance, with 43.24% and 36.29% of the total variance respectively. IntercoolerCoreDP is next with 8.05% of the contribution and IntercoolerHX_ effect is next with 7.82%. Lastly is IntercoolerNondimensionalWeight with 1.61% of the contribution. Based upon this information, planned experimentation would aim to gather data that would better characterize either IntercoolerBleedFlow or LPCPR so the uncertainty around their impacts could be reduced and, therefore, their overall impact reduced as well.

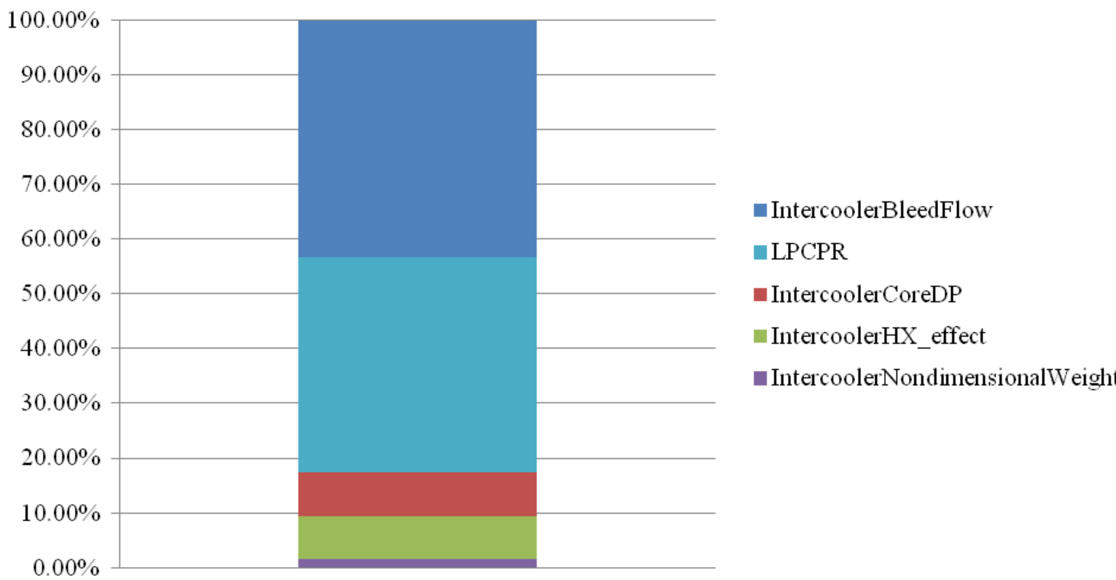

Figure 86: Contribution of T22.1 technology impacts to NOx emissions variance.

Once the experiment standards and the required measurements have been identified, the overall purpose of the experiment can be finalized. The overall purpose can be identified from the list of experiment objectives provided in the experiment taxonomy in Table 6. For T22.1, it was determined that the purpose is both model construction and uncertainty reduction. Since the technology is only at TRL 3, the results will be used to build detailed technology-level performance models. At the same time, the results will be used to reduce the uncertainty surrounding the technology impacts used in the system level modeling environment. Referencing the uncertainty taxonomy provided in Figure 23, the uncertainty sources this experiment will address are physics characterization and measurement.

The last aspect of experiment design is tracking the uncertainty reduction as information is gathered and knowledge is gained. It was proposed that uncertainty thresholds could be put in place for each TRL. This implies that achieving a TRL level depends on not only the quality of the experimentation but also the knowledge gained from each experiment. While attempting to implement this process an issue arose regarding how the thresholds should be defined. It was observed in the previous subsection that it is difficulty to quantify the amount of uncertainty associated with a single technology for multiple reasons. Tracking at the technology impact level can be misleading when comparing distributions of multiple impacts. In contrast, comparing at the system level for only a single impact can be misleading as well due the different ways a technology can impose an impact, or lack of impact, to an objective metric.

Based on these observations, it was determined that uncertainty thresholds would be applied for each technology at the technology impact level to track technology-specific progression. Furthermore, the uncertainty impact at the system level would be tracked to compare the progression of multiple technologies at once. Setting the thresholds requires a starting point, which may not be available until some information on a technology is available. Therefore, once enough information is available to map a technology to a set of k-factors and define the starting uncertainty levels, the thresholds for future TRLs can be defined. It is acknowledged that this may not be feasible until a technology has already achieved a TRL of 2 or 3. For this research, the current TRL and impact uncertainty for each technology has already been provided so it can be used as the starting point.

For T22.1, experimentation that meets the previously defined standards to achieve

TRL 4 should be planned. The purpose of the experiment is to further quantify the IntercoolerBleedFlow and LPCPR impacts, so relevant measurement devices are selected. After the experiment is conducted, uncertainty will be reduced due to the improvement in test article and environment fidelity, the use of the data for model building and validation purposes, and the overall knowledge gained about how the technology will operate. The experiment design process formulated and implemented for T22.1 is outlined in Figure 87.

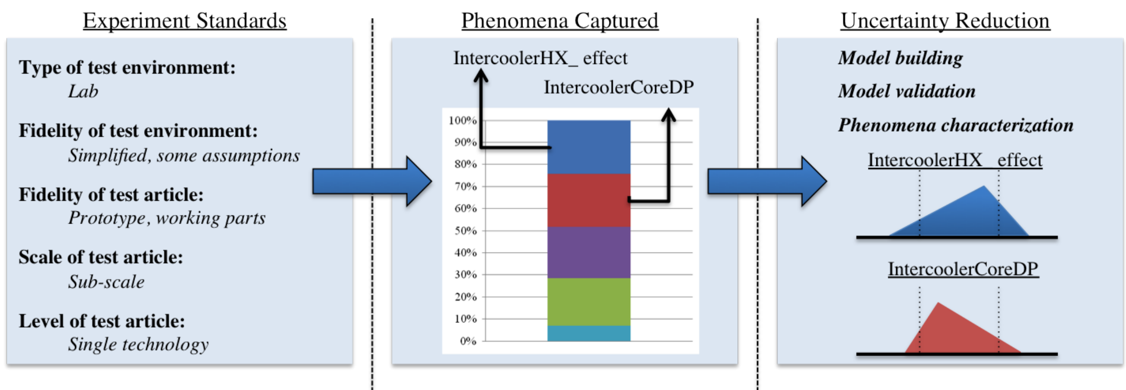

Figure 87: Experiment design process implemented for T22.1.

The reduction in uncertainty achieved by the planned experiment on T22.1 was simulated to demonstrate how the prioritizations can change over time. It was assumed that the planned experiment reduced uncertainty relating to the LPCPR impact for T22.1. After the reduction was simulated, the P-OAT experiments and T-OAT experiments we re-conducted and new variance contribution waterfall charts were created. Figure 88 provides the new variance contributions for T22.1. On the left side is the original variance waterfall and on the right side is the waterfall after the uncertainty was reduced. It is observed that approximately 70% of the total NOx emissions uncertainty for T22.1 has been reduced, and a majority of the remaining uncertainty is contributed by IntercoolerHX_ effect. Therefore, the next experiment planned for T22.1 would focus on gathering data to better quantify the IntercoolerHX_ effect impact.

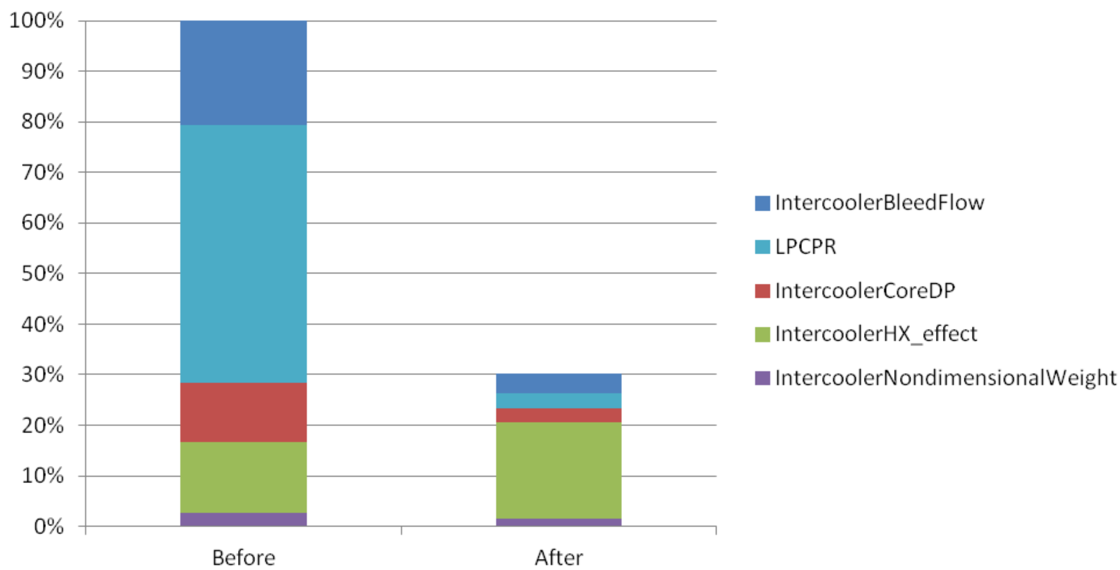

Figure 88: Change in variance contributions for T22.1 technology impacts after uncertainty is reduced.

Figure 89 provides the new variance contributions for the portfolio as a whole. The original variance waterfall is provided on the left side the and the new variance waterfall is on the right. It is observed that the approximately only 30% of the original NOx uncertainty remains after the T22.1's uncertainty reduction occurs. Furthermore, it is observed that T22.1 and T40 now contribute approximately the same amount to the remaining NOx uncertainty. Therefore, the next experiment planned based on NOx emissions prioritization would focus on either of those two technologies.

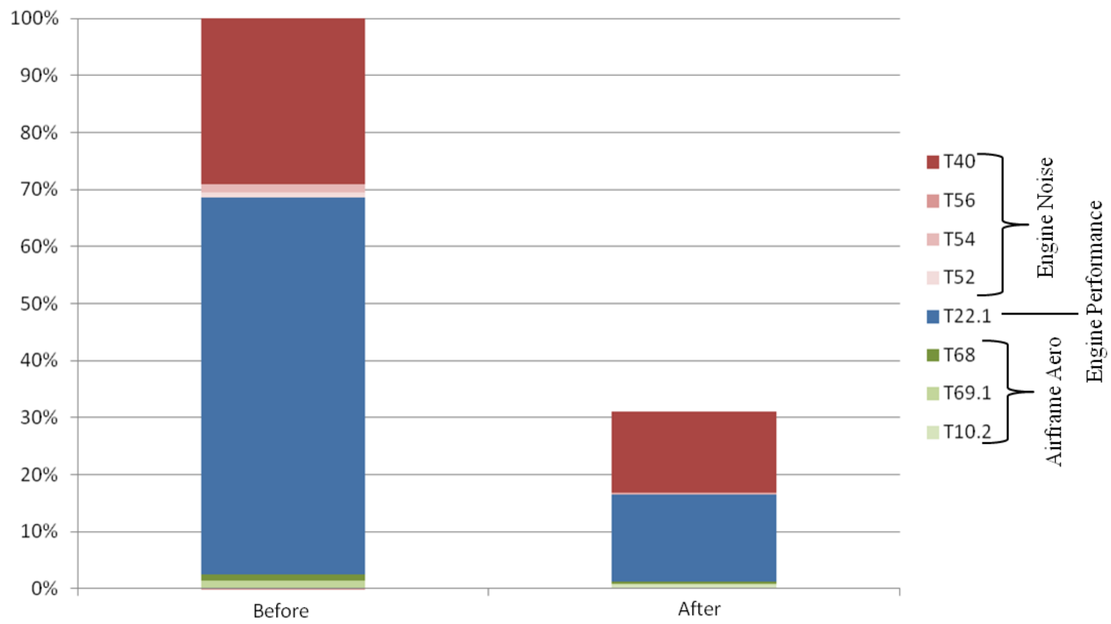

Figure 89: Change in variance contributions for Technology Portfolio 2 after uncertainty is reduced.

6.1.2.3 *Observations and Discussion*

The outlined experiment planning process is an iterative process and should be continued until resources are expended, time has run out, or all technologies have reached the desired readiness levels. There are two iteration loops that occur within the process. The first loop is with the prioritization of the technologies. As experiments are planned and executed, information will come in that causes the technology prioritization to change. Therefore, this assessment should be repeated throughout development. The second iteration loop deals with available resources. When an experiment is planned for a specific technology, The amount of technology impacts investigated in an experiment for a single technology depends on the amount of available resources for that experiment. Therefore, if an experiment is planned for a single impact and resources are still available, the experiment can be altered to include additional measurements that aim to quantify another impact. Likewise, the additional resources could also be used to plan a completely separate experiment for another high priority technology identified by the prioritization assessment.

For technology prioritization according to performance risk, it was observed that very similar results are provided through the use of POS information and variance information. Combining the information provided by the two measures enables communication of all relevant performance risk information. Therefore, Hypothesis 3.1 is confirmed.

For readiness risk, the information provided by the current TRL and the number of years until TRL 9 is achieved provides likelihood and difficulty measure for readiness. Furthermore, it was shown that these measures can be used together to perform the identified readiness risk tradeoffs and enable the selection of a technology for further experimentation. Based on these observations, Hypothesis 3.2 is confirmed.

Finally, the implementation of the proposed experiment design methodology demonstrated how the above information paired with the morphological analysis would be used to create an experiment plan. It was noted in Chapter Four that an experiment is defined by the test article, test environment, and the purpose of the test. It was demonstrated that the proposed process is able to identify relevant choices for each of these defining characteristics. Therefore, Hypothesis 3.3 is confirmed.

6.2 Examination of Phase 4

A set of experiments was conducted to test Hypotheses 4.1 and 4.2. This phase of development involves tracking the development progress of each technology in the selected portfolio as experimentation are performed and knowledge is gained. Figure 90 provides the finalized process for *Technology Transition Assessment*, which involves risk assessments at both the technology-level and portfolio-level. Recall, it was hypothesized that it would be sufficient to track risk progression at the technology-level only. However, the following experiment results and discussion will demonstrate why analysis at both levels is necessary.

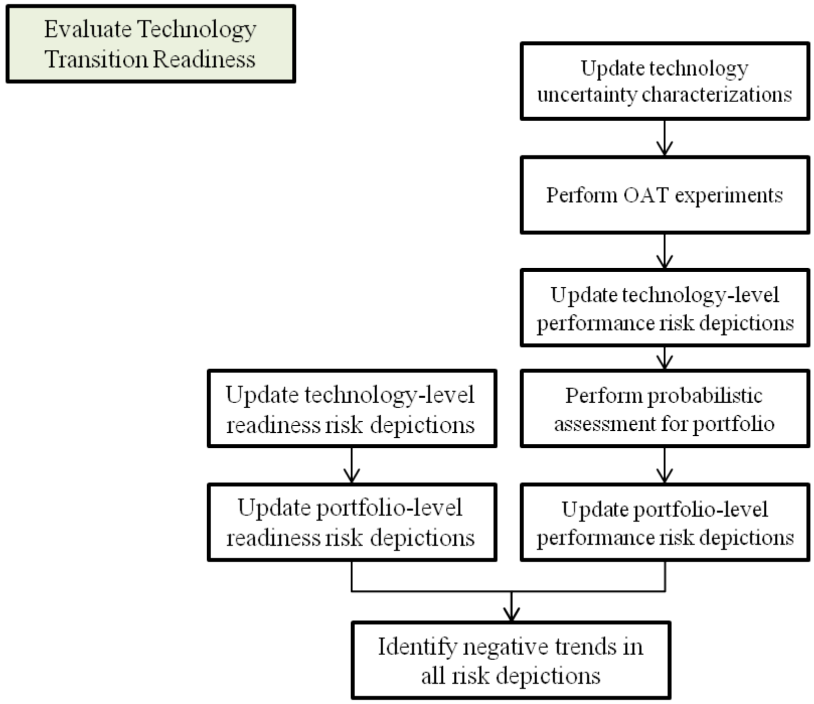

Figure 90: Process flowchart for technology transition assessments.

6.2.1 Performance Risk Progression for an Individual Technology

While it was established that no single technology will enable the performance goals to be met, it is still important to track how they are progressing on an individual basis. With respect to performance, a technology is selected for transition based upon their expected performance and the remaining performance uncertainty. For the uncertainty, it is important to understand how much remains and also how it is impacting the expected performance of the technology.

For this experiment, technologies were analyzed individually and the progression of their readiness risk and performance risk was tracked. Technologies included in Portfolio 2 from the previous experimentation were utilized for this analysis and the triangular distributions for each technology's impacts defined during Phase 2 were utilized as the starting point or baseline performance risk analysis. Progression scenarios were created by forming new triangular distributions for each impact of each technology. Each new distribution was defined by randomly selecting new minimum values, maximum values, and mid-points. The points were selected in a manner that ensures the technology-level uncertainty reduces. Therefore, the minimum points will increase, the maximum points will decrease, and the mid-points will always be between the newly defined minimum and maximum values.

The progression scenarios for each technology were determined on an individual basis. Ten different scenarios were created for each technology and the uncertainty distribution for each impact of each technology had to be simulated for the progression scenarios. T10.2 will be used to demonstrate the uncertainty reduction and it is mapped to four k-factors: TransREHT, TransREVT, HPX_ map_ highAlt, and WAC. The progression scenarios for T10.2 are shown in Table 25, Table 26, Table 27, and Table 28 for each of the k-factors respectively. The minimum values, maximum values, and mid-point values are provided for each triangular distribution. Additionally, the variance of each triangular distribution is provided. It is clear through observation that the variance for each k-factor decreases from one case to the next until the value for the k-factor stabilizes to a single value with no uncertainty. By Case 7 of the reduction scenario each k-factor has stabilized.

Table 25: Progression scenarios for T10.2 k-factor TransREHT.

Case	Min	Mid	Max	Variance
Baseline	16	20	24	2.667
1	16.181	16.28	20.206	0.878
2	16.185	16.187	16.609	9.94E-03
3	16.185	16.186	16.188	3.89E-07
4	16.185	16.185	16.186	5.56E-08
5	16.185	16.185	16.185	0
6	16.185	16.185	16.185	0
7	16.185	16.185	16.185	0
8	16.185	16.185	16.185	0
9	16.185	16.185	16.185	0
10	17.185	17.185	17.185	0

Table 26: Progression scenarios for T10.2 k-factor TransREVT.

Case	Min	Mid	Max	Variance
Baseline	16	20	24	2.667
1	16.092	16.124	20.12	0.894
2	16.095	16.103	16.174	3.152E-04
3	16.095	16.096	16.106	6.167E-06
4	16.095	16.095	16.097	2.222E-07
5	16.095	16.095	16.095	0
6	16.095	16.095	16.095	0
7	16.095	16.095	16.095	0
8	16.095	16.095	16.095	0
9	16.095	16.095	16.095	0
10	16.095	16.095	16.095	0

Table 27: Progression scenarios for T10.2 k-factor HPX_ map_ highAlt.

Case	Min	Mid	Max	Variance
Baseline	35	78.841	125	337.575
1	35.972	39.514	79.955	99.515
2	36.206	36.686	41.01	1.167
3	36.248	36.253	37.06	0.036
4	36.248	36.252	36.294	1.082E-04
5	36.248	36.249	36.254	1.722E-06
6	36.248	36.248	36.249	5.556E-08
7	36.248	36.248	36.248	0
8	36.248	36.248	36.248	0
9	36.248	36.248	36.248	0
10	36.248	36.248	36.248	0

Table 28: Progression scenarios for T10.2 k-factor WAC.

Case	Min	Mid	Max	Variance
Baseline	1.1	1.1	1.2	5.556E-04
1	1.1004	1.1008	1.1059	1.567E-06
2	1.1004	1.1004	1.101	2.000E-08
3	1.1004	1.1004	1.1004	0
4	1.1004	1.1004	1.1004	0
5	1.1004	1.1004	1.1004	0
6	1.1004	1.1004	1.1004	0
7	1.1004	1.1004	1.1004	0
8	1.1004	1.1004	1.1004	0
9	1.1004	1.1004	1.1004	0
10	1.1004	1.1004	1.1004	0

Tracking the progression of a single technology at the k-factor level does not provide information about how the objective metrics are affected. Rather, it only provides information about how much uncertainty is being reduced and how the expected value of the k-factors are affected. Identifying the changing impact of the technologies is facilitated by re-conducting the previously discussed OAT experiments. Recall, in the OAT experiments a single non-baseline technology was turned on at a time and the system level performance was analyzed. Now, however, the OAT experiments are not performed just once for each technology. Rather, they are conducted for each case within the defined reduction scenarios.

For the OAT experiments, the uncertainty defined for each case of the reduction scenario was again propagated to the three objective metrics using 50,000 case Monte Carlo analyses with the previously defined ANNs. As expected, the variance of the objective metrics decrease with each proceeding case in the reduction scenario. This uncertainty reduction is shown in Figure 91 for all three objective metrics. In this depiction, the x-axis is representative of time progressing and knowledge gained through experimentation. The variance of pdfs for the objective metrics shrinks from one case tot he next and the expected value shifts to the final stabilized value. For fuel burn reduction, the mean shifts down, which indicates degrading expected performance. In contrast, the mean shifts upwards for the noise margin and NOx emissions which indicates favorable performance progressions.

Next, the relevant performance risk measures defined during Phase 2 were calculated for each case of T10.2's reduction scenario. The performance risk results for fuel burn reduction are shown in Figure 92. It is quickly evident that the use of POS to analyze performance risk of a single technology is not helpful because there will likely be no chance of meeting the goals with a single technology. Therefore, the results shown for S/N are much more interesting. The top two sub-figures of Figure 92 provide the performance risk results with S/N as the measure of likelihood.

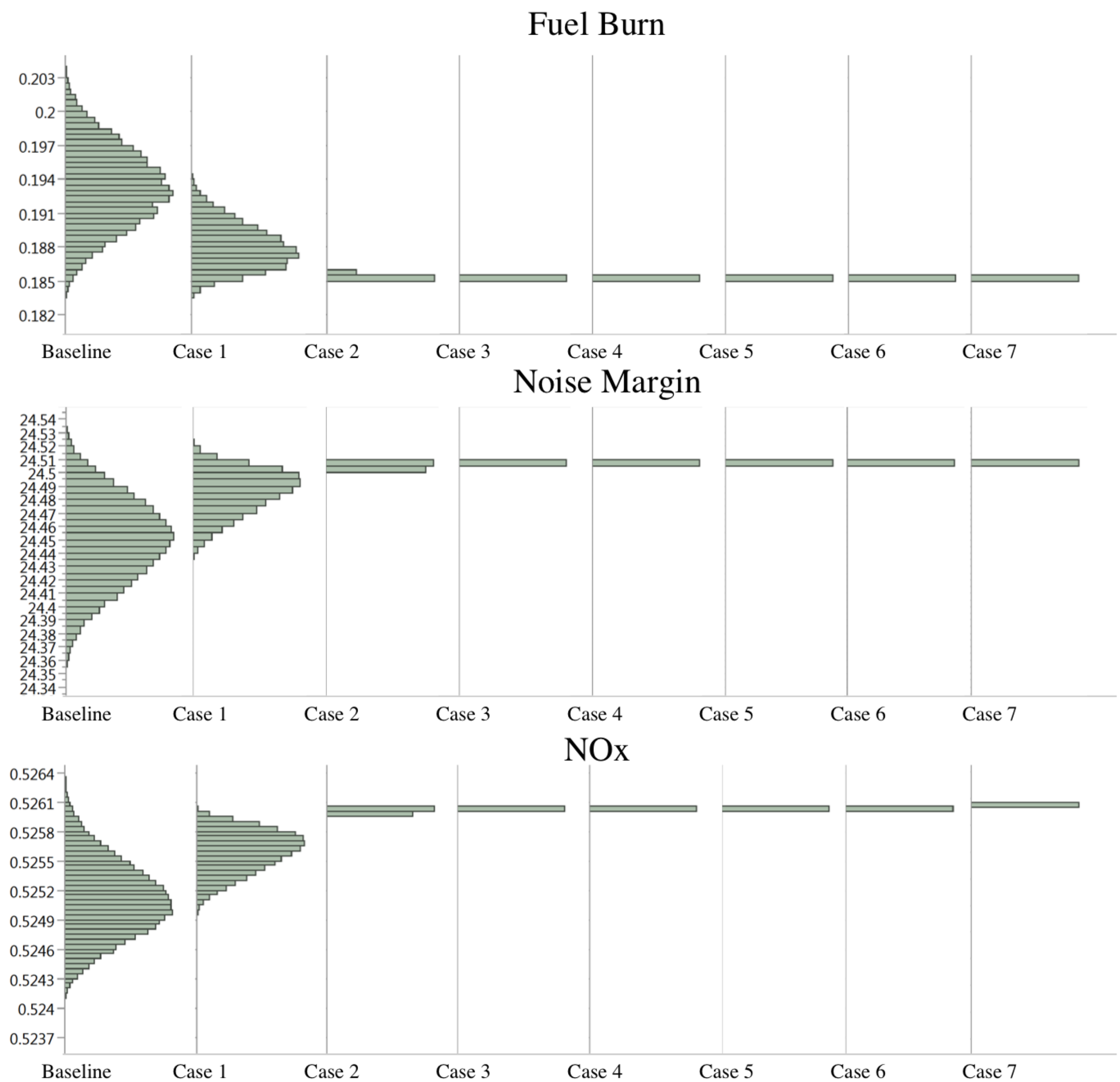

Figure 91: Uncertainty reduction progression of objective metrics' PDFs for T10.2.

S/N decreases with each reduction in uncertainty, which may be unexpected because a decrease in uncertainty should correspond to an increase in S/N. However, this would only hold true if the mean of the metric were remaining constant or improving. Therefore, this is indicative of a degrading mean value, which was already observed in Figure 91. The progression of risk was observed to be increasing as uncertainty decreases according to the S/N versus TCE subfigure. For S/N versus TCE, the baseline case in T10.2's reduction progression provides the lowest performance risk and the risk increases with each uncertainty reduction case until it stabilizes in the bottom left corner.

S/N versus WPV for fuel burn reduction tells a different story for this reduction scenario. The values for WPV appear to increase for each proceeding case in the reduction scenario. This is interesting because one would expect the WPV's to decrease along with the mean values. However, as Figure 91 displays, a shift in the mean paired with a reduction in uncertainty does not mean the tails of the distribution will also shift proportionally. Therefore, while the baseline case for T10.2 provides the best expected fuel burn performance, the final case provides best worst-case scenario performance.

Figure 93 provides T10.2's noise margin performance risk depictions. Similarly to the fuel burn assessment, the POS for noise margin is 0% and the TCE values represent the mean of the entire distribution. In contrast, the trends in the S/N subfigures are much different than those observed for fuel burn reduction. As uncertainty is reduced, the S/N values increase which is indicative the improvement in expected noise margin that was observed in Figure 91. For both S/N subfigures, the performance risk decreases because the final case of the reduction scenario is in the top right corner. Therefore, both the mean of the distribution and the left tail are shifting towards the right.

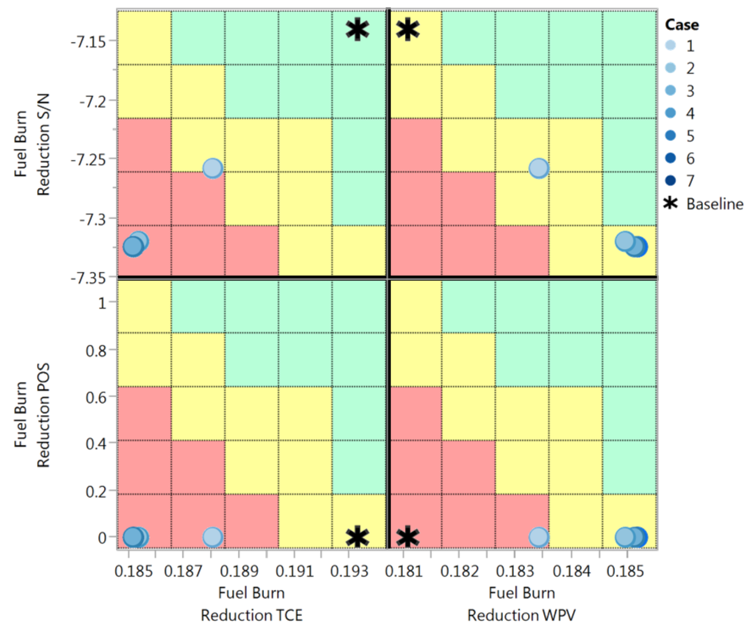

Figure 92: Fuel burn reduction performance risk for T10.2 as uncertainty is reduced.

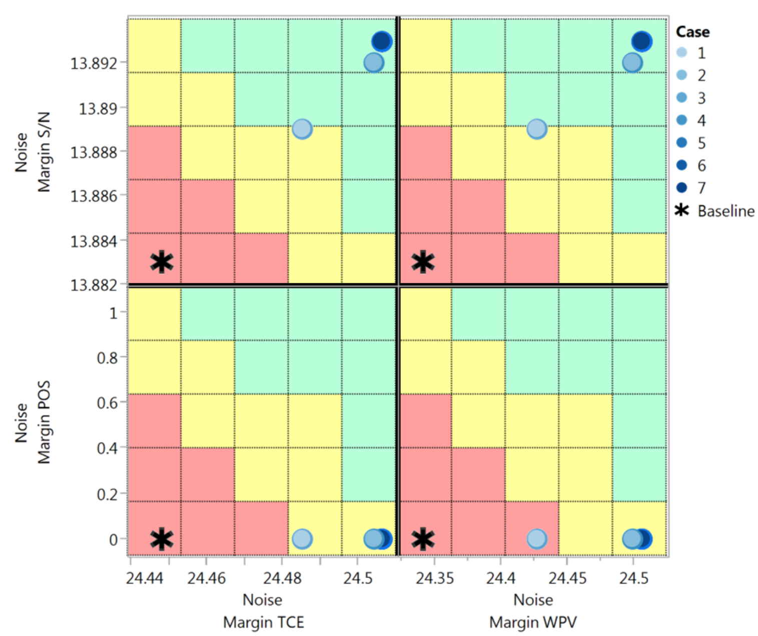

Figure 93: Noise margin performance risk for T10.2 as uncertainty is reduced.

Recall, it was hypothesized that it is important to track the amount of technology performance uncertainty as well as the progression of the exact impact. Therefore, a separate performance risk formulation was created and is shown in Figure 94. In this depiction the variance is used directly to represent the measure of likelihood and the mean is used to represent the performance, which could be used as a measure of difficulty. Mean and variance were not utilized in previous sections because it was desired to show information at the portfolio-level and measures such as S/N and POS had the ability to provided more information. However, now that the progression of a single technology is of interst this formulation provides a depiction of how the mean changes as the uncertainty reduces. Furthermore, it provides an explicit representation of how much uncertainty has been reduced and how much remains.

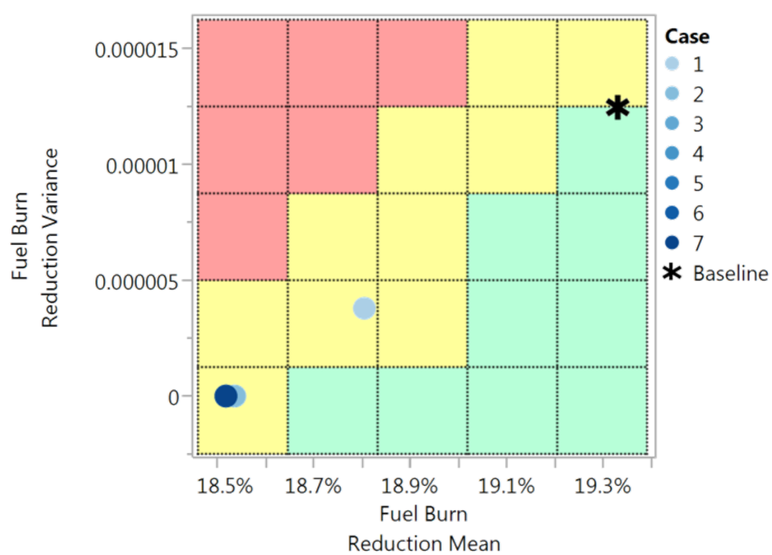

Figure 94: Fuel burn reduction mean versus variance for T10.2 as uncertainty is reduced.

Observing the results shown in Figure 94, it is clear that as the uncertainty reduced for T10.2, its fuel burn performance degraded. This observation agrees with the previous observations made regarding T10.2. Furthermore, it is realized that there is little to no uncertainty left surrounding the fuel burn metric. This would indicate to decision makers that the expected performance impact of T10.2 on fuel burn reduction has no chance of improving in the future.

Based upon these observations, communication of the shifting of the mean of an objective metric as the uncertainty is reduced is important for decision makers to understand the progression of a technology over time. This can be accomplished by tracking the mean of the objective metric and the variance of the objective metric on a performance risk depiction. This information can be obtained by repeating the OAT assessments for each technology within the portfolio as time progresses and experiments are performed.

6.2.2 Performance Risk Progression for a Technology Portfolio

In addition to tracking the progress of technologies on an individual basis, the progress of the portfolio as a whole can be tracked as well and utilized for transition assessments. As experimental data becomes available and technology-level uncertainty distributions are updated, system level assessments must be re-conducted to provide and updated picture of how the portfolio is performing. The updated technology-level distributions will have an impact on the system level performance distributions and, in turn, the performance risk.

It was demonstrated in the previous subsection that the reduction in a technology's performance uncertainty can affect the system level performance in different ways. Furthermore, the way the uncertainty reduction materializes can also be drastically different. In order to demonstrate the different ways uncertainty can reduce for a given technology portfolio, different reduction scenarios were created. Portfolio 2 from Experiment Set 2 was utilized for this experiment. Recall, the technologies in Portfolio 2 map to a total of 17 probabilistic EDS k-factors. A baseline triangular probability distribution was set for each k-factor based upon the provided 3-point estimates for each technology. Next, six different reduction scenarios were created by randomly selecting new minimum values, maximum values, and mid-points for each k-factor that ensured a reduction in the k-factor's variance. The uncertainty depictions for the baseline scenario and reduction scenarios are provided in Figure 95. Note that these reduction scenarios are different than the ones from the previous subsection because they are not supposed to demonstrate a progression. Rather, each reduction scenario is meant to be a different potential reduction from the baseline uncertainty depiction.

Next, the k-factor uncertainty was propagated to the system level through 50,000 case Monte Carlo analyses with the previously defined ANNs. The results of the Monte Carlo analyses enabled the calculation of relevant statistics for the three objective metrics. Figure 96 provides the mean versus variance for each of the three objective metrics. The black star represents the baseline and each of the colored points represent the reduction scenarios. It is clear that the variance decreases for each of the reduction scenarios, which is expected. However, the change in the mean performance is not consistent for the reduction scenarios as each objective metrics has reduction scenarios with both improved performance and degrading performance. Therefore, it was accepted that these six reduction scenarios are adequate for this experimentation because they provide a variety of potential performance outcomes.

Figure 97 shows the performance risk depictions for the baseline scenario and six reduction scenarios of Portfolio 2. Unlike the technology-level assessments conducted in the previous subsection, POS is now a relevant measure of likelihood because the performance is representative of the entire technology portfolio. For fuel burn reduction, it is observed that the POS increases for each of the reduction scenarios. This is not true for S/N. Half of the reduction scenarios provide an increase in S/N while the other half provide a reduction.

During the technology-level assessments, it was established that the change in S/N from one case to the next was driven by the mean value since each proceeding

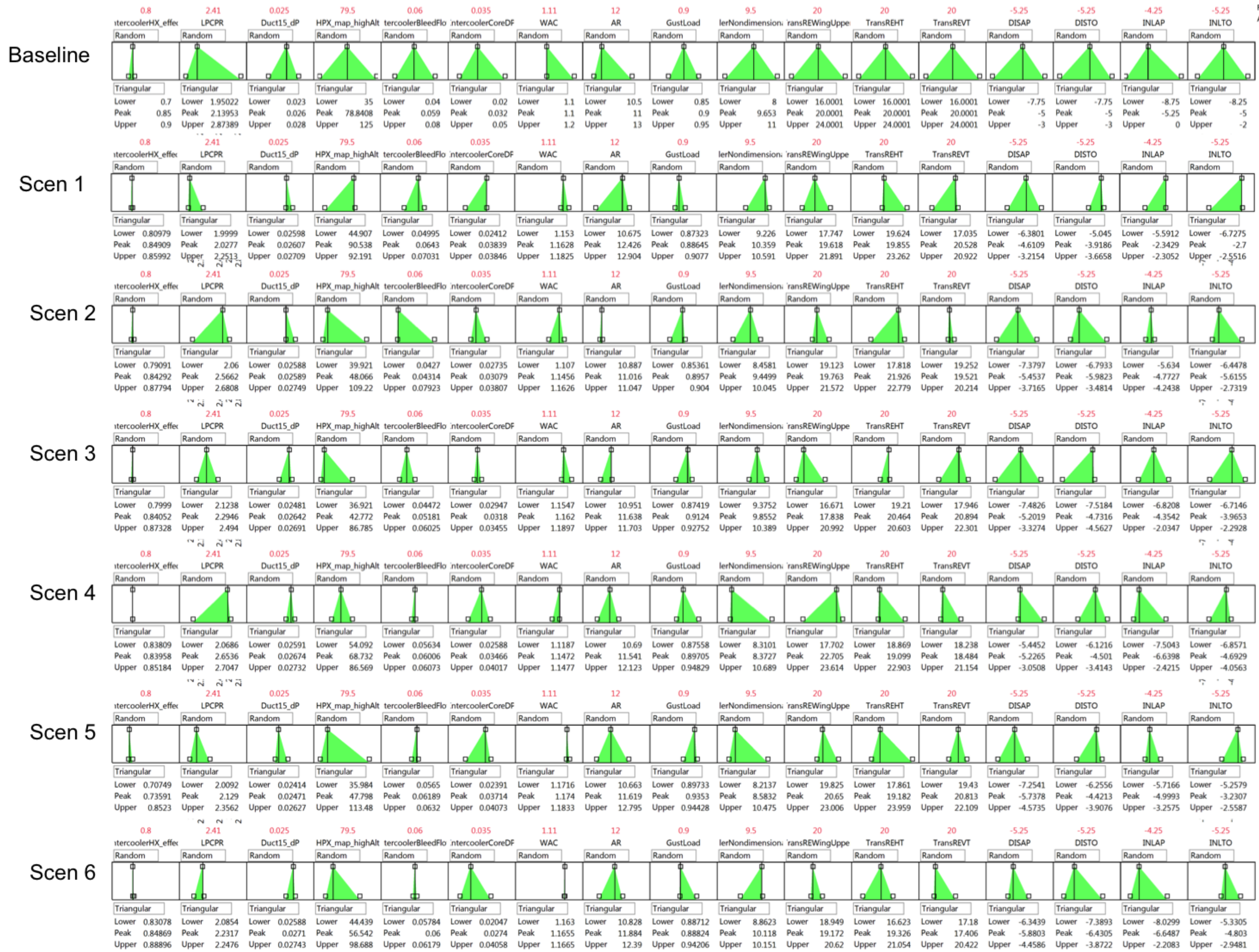

Figure 95: Potential uncertainty reduction scenarios for the selected technology portfolio.

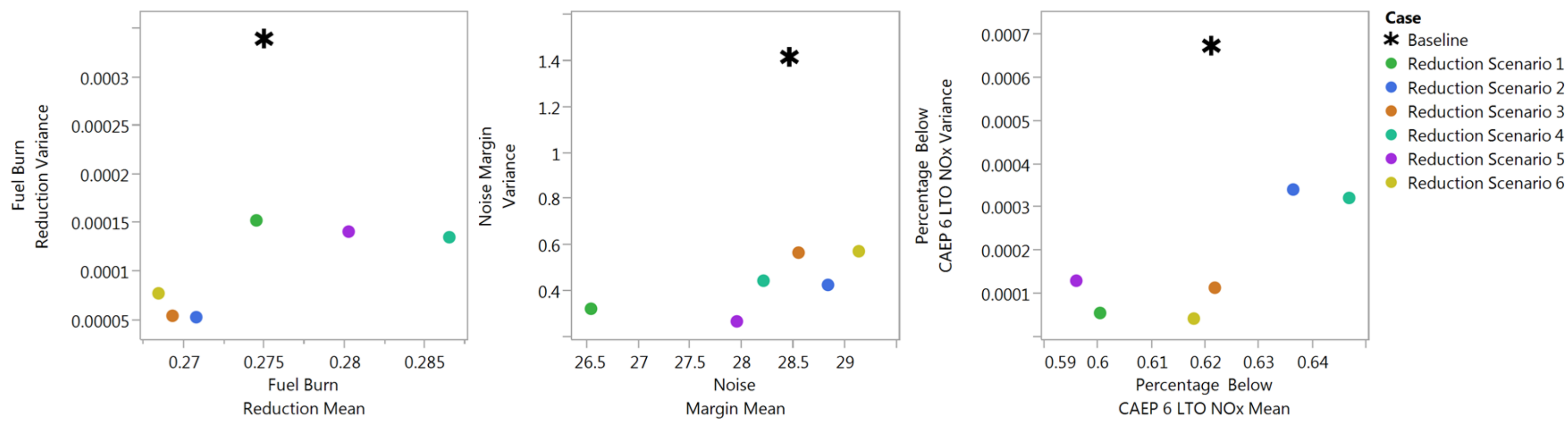

Figure 96: Mean and variance progression for reduction scenarios.

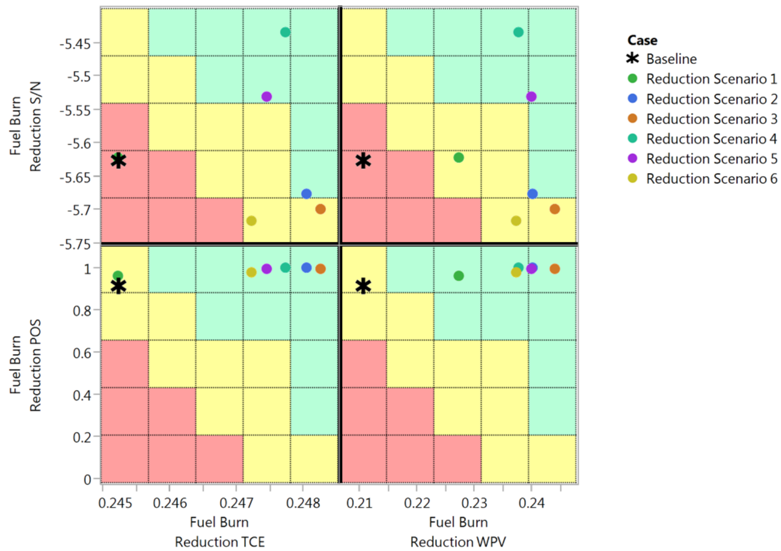

Figure 97: Fuel burn reduction performance risk for reduction scenarios.

case had a known decrease in variance. However, this same conclusion can not be strictly used for the results shown in Figure 97, Figure 98, and Figure 99 because of the unknown comparative variance among the reduction scenarios. While it is known that the variance of each reduction scenario is smaller than the variance of the baseline, nothing can be said about the variances of the reduction scenarios when compared to each other. Therefore, if a reduction scenario has a S/N less than the S/N of the baseline, it can be assumed its mean value is less favorable. However, it cannot be safely assumed that Reduction Scenario 1 has a more favorable mean value than Reduction Scenario 5 solely based upon S/N because the noise margin variance of Reduction Scenario 5 may be greater than that of Reduction Scenario 1, which could also drive the S/N down.

Based upon these observations, it is practical to use POS instead of S/N to communicate the performance likelihood and represent the uncertainty in the assessment. The WPV provides an indication of how the uncertainty is affecting the tail of the distribution and can be used with POS to provide a complete depiction of the portfolio's performance.

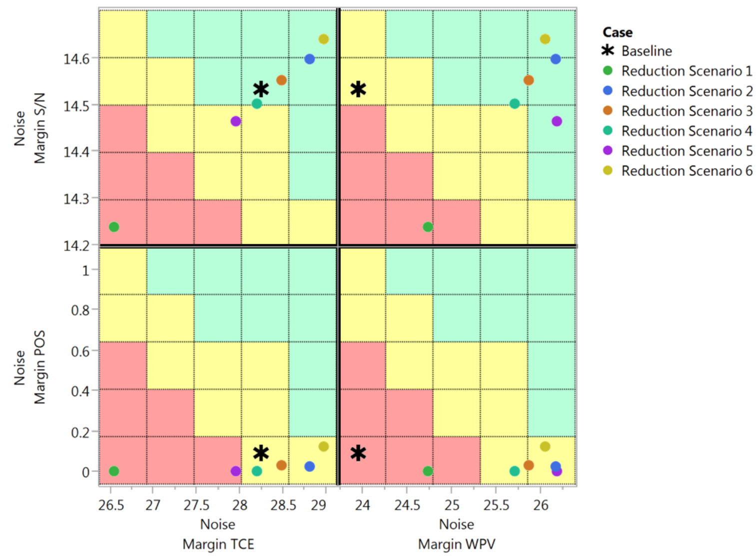

Figure 98: Noise margin performance risk for reduction scenarios.

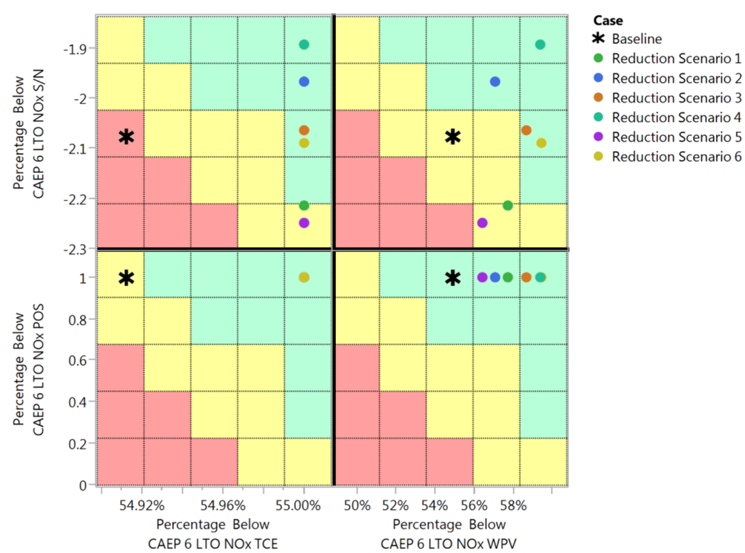

Figure 99: NOx emissions performance risk for reduction scenarios.

6.2.3 Readiness Risk Progression

Tracking readiness risk in terms of the previously defined metrics does not require any intensive analysis. Recall, it was previously determined that readiness risk for an individual technology can be tracked through TRL and the number of years until TRL 9 is achieved (or a similar difficulty measure). As time progresses, the number of years will decrease accordingly and the TRL will increase. If the initial assignment of difficulty is correct, the readiness chart will only need updated when a new TRL is achieved or another year passes. However, this may not always hold true.

Figure 100 displays an ideal and non-ideal progression of readiness risk for a single technology. As the ideal trend shows, the TRL should increase and the difficulty should continuously decrease accordingly. It will hold true that the TRL will increase and not decrease over the course of time, but the rate at which it increases can vary. The ideal trend in Figure 100 shows that the number of years until TRL 9 is achieved is continuously decreasing; however, this is not what will always happen.

Assignment of the number of years until TRL 9 is achieved is a SME-based process. Therefore, when an SME assigns this value they are doing so based upon their current knowledge of the technology's status and what it will take to further the development. However, as experiments are performed and more information becomes available, the SME assessment may change. In this context, an SME may wish to increase or reduce the number of years, which will affect the technology's readiness risk.

Determining when a technology's readiness risk is re-assessed is important. It is important to re-assess the readiness risk measures both when new information becomes available and on a regularly set schedule. For example, the number of years until TRL 9 is achieved should never be reduced simply because time has progressed. If over the course of the year no new experimental data has been collected for a technology, the SMEs should re-assess the number and determine if the it should be reduced in actuality. Furthermore, when experiments are conducted and a new TRL

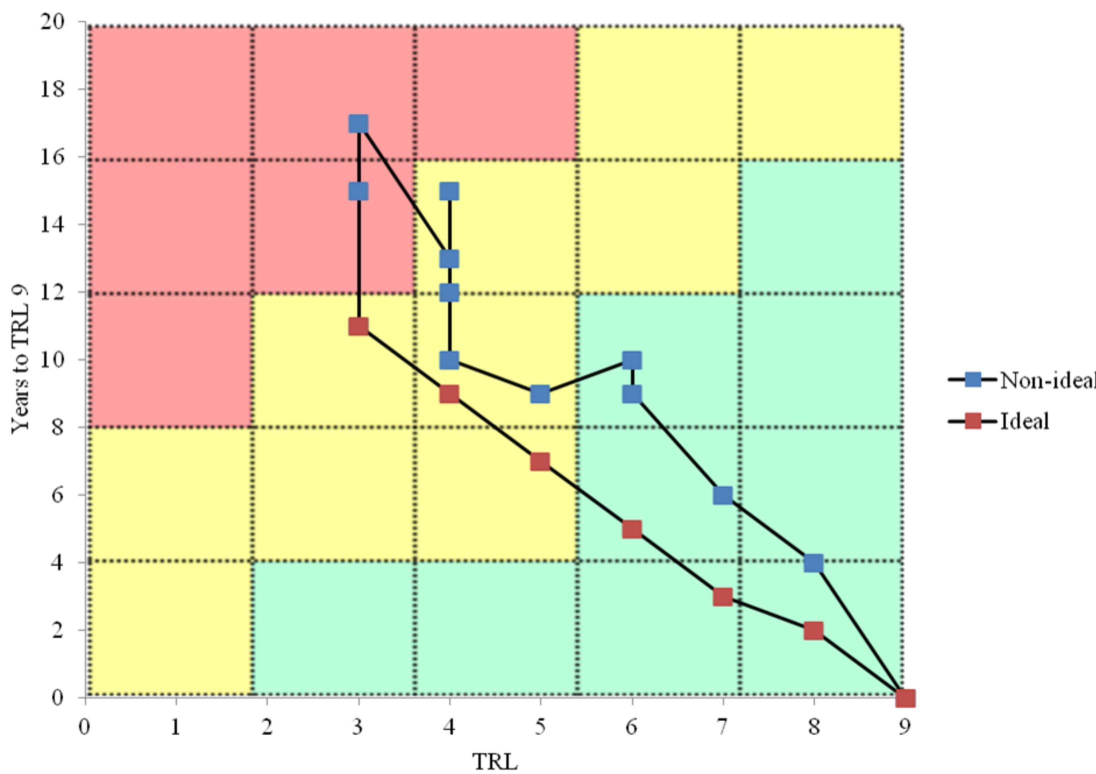

Figure 100: Readiness risk reduction trends for a single technology.

is achieved the number of years should also be re-assessed because the new TRL may have been achieved in a fewer or greater number of years than originally expected.

The non-ideal trend displayed in Figure 100 shows two different ways the readiness risk could progress in a less than favorable manner. First, note that the starting readiness risk is a TRL of 3 with 11 years until TRL 9 is achieved. The first progression is a jump in the number of years, from 11 to 13, with no movement in TRL. This is not ideal because it means unexpected risk has occurred when trying to achieve TRL 4. This trend is observed again at TRL 4. When TRL 4 is first achieved it is estimated that there are 13 years left until TRL 9 is achieved. However, that number jumps up to 15 years before finally decreasing to 12 years and eventually 10 years. Once TRL 5 is achieved, the number further reduces to 9 years.

In addition to an increase in the number of years while TRL remains constant, the number of years can also increase even if the TRL itself is increasing. This is shown in Figure 100 when going from TRL 5 to TRL 6. This would be indicative of a situation where TRL 5 took longer than expected or something was learned during TRL 5 that indicates TRL 6 will take longer than expected.

Enumeration of these trends before they are observed enables decision makers to understand when a technology is progressing in a less than favorable way with respect to readiness risk. Similarly, ideal and non-ideal trends can be observed at the portfolio level. It was established that aggregate TRL and difficulty measures enable the communication of readiness risk for an entire portfolio. The aggregate readiness risk will change when a single measure is altered for a single technology. Therefore, the readiness risk for the entire portfolio should be updated when the readiness risk for a single technology is updated.

In an ideal world, the readiness risk of all technologies will reduce at a favorable rate over time which will cause the readiness risk of the portfolio to continuously shrink as well. However, it was established that the readiness risk of the technologies can change in a variety of ways. Therefore, one technology can have a significant increase in readiness risk while another has a significant decrease. It may be difficult to identify when this occurs by only observing risk through the aggregate measures.

A readiness risk reduction scenario was created for each of the technologies in Portfolio 2 to demonstrate how the aggregated readiness risk is affected. Table 29 and Table 30 displays the simulated readiness risk progression for each of the technologies. Note that T22.1 has a non-ideal risk progression, T54 has an extremely favorable risk progression, and all other technologies have ideal progressions. These reductions were used to calculate the readiness risk progression for the entire portfolio.

Table 29: Readiness risk reduction scenario for a technology portfolio, Part 1.

T22.1		T40		T52		T54	
TRL	Years	TRL	Years	TRL	Years	TRL	Years
3	11	3	11	6	6	7	3
3	15	4	8	6	6	8	1
3	17	5	6	7	5	9	0
4	13	6	4	8	3	9	0
4	12	7	3	8	0	9	0
4	15	8	2	9	0	9	0
4	10	9	0	9	0	9	0
5	9	9	0	9	0	9	0
6	10	9	0	9	0	9	0

Table 30: Readiness risk reduction scenario for a technology portfolio, Part 2.

T56		T10.2		T68		T69.1	
TRL	Years	TRL	Years	TRL	Years	TRL	Years
3	15	5	12	4	10	4	12
4	10	5	10	5	6	5	6
5	6	6	8	5	6	5	6
6	3	6	7	6	4	6	4
7	2	7	5	7	3	7	3
8	1	8	2	8	2	8	2
9	0	9	0	9	0	9	0
9	0	9	0	9	0	9	0
9	0	9	0	9	0	9	0

Figure 101 and Figure 102 show two different readiness risk progressions, the first using the sum of years until TRL 9 is achieved and the second using the average years. The trend observed in Figure 101 shows a steadily decreasing readiness risk because the TRL increases as the number of years decreases. At the end of the trend, there is a slight increase in risk but it is not very noticeable.

In contrast, the trend shown in Figure 102 accentuates the increase in readiness risk at the end of the progression. Additionally, it shows a slight increase in readiness risk from the second point to the third point. Therefore, when using the average number of non-zero years an increase in readiness risk for a single technology is more noticeable at the portfolio level because fully developed technologies are not considered.

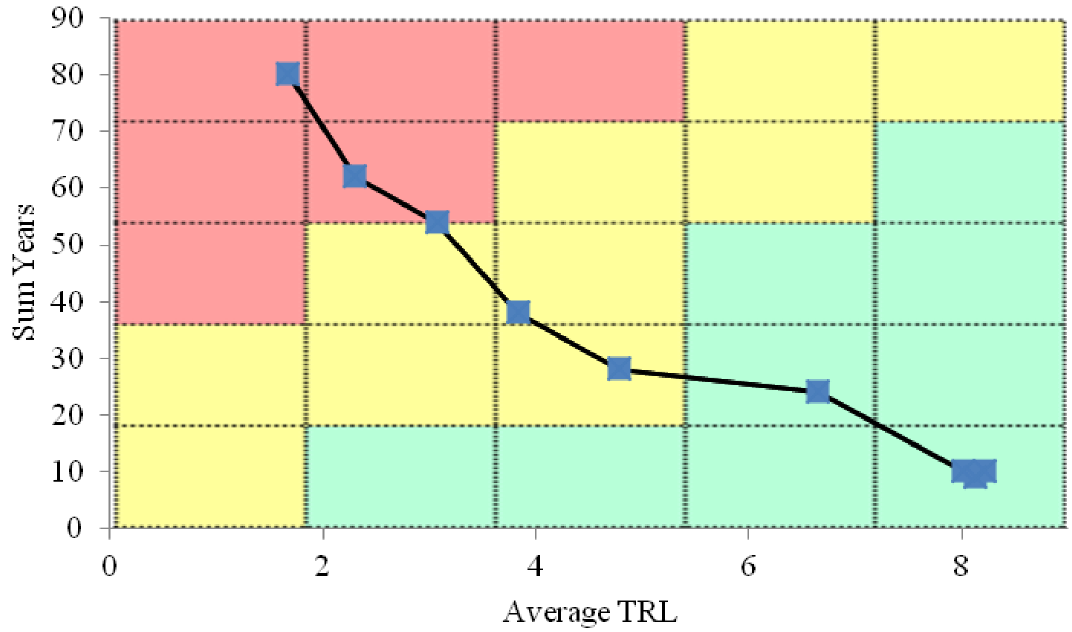

Figure 101: Readiness risk reduction for a technology portfolio using the summation of years as a measure of difficulty.

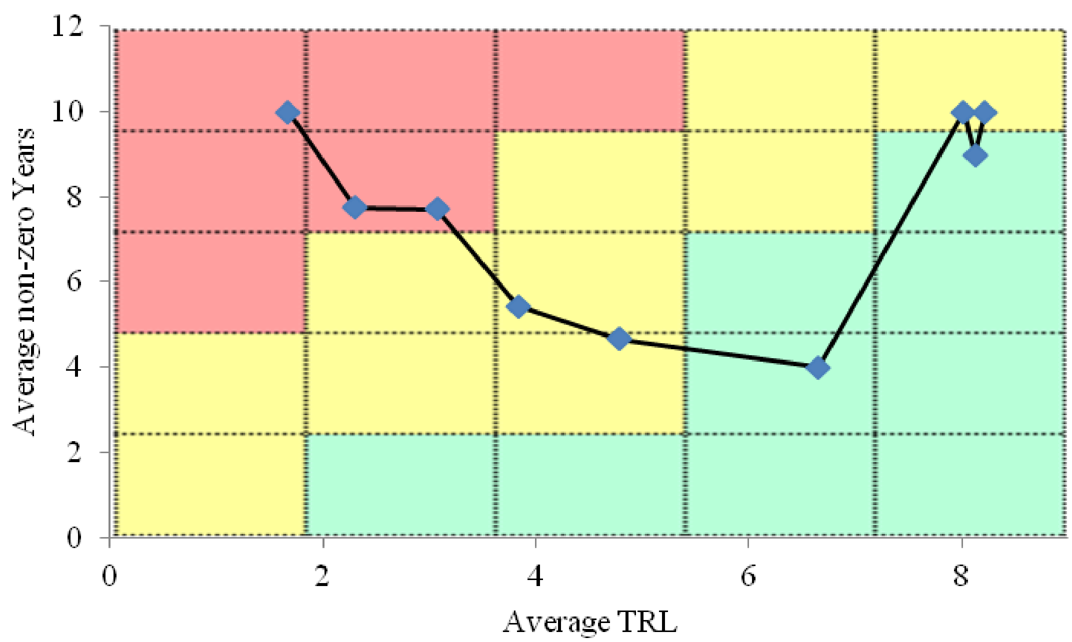

Figure 102: Readiness risk reduction for a technology portfolio using the average number of years as a measure of difficulty.

6.2.4 Observations and Discussion

It was demonstrated how performance risk and readiness risk can be tracked at both the technology-level and the portfolio-level. Furthermore, it was established that observing risk solely at the portfolio-level or technology-level may not communicate the entire story. For performance risk, assessments at both levels is important because the beneficial impacts of a single technology may be overshadowed by the detrimental impacts of another technology. While both may provide the performance they were selected for, their combined performance may no longer provide the required benefits. For readiness risk, assessments at both levels are important because a risk increase for one technology may cause a decision maker to be more alarmed than necessary. A significant decrease in readiness risk for one technology may open resources that can be invested in a high risk technology. Therefore, it is observed that it can be important to track readiness risk at both levels.

The progression of a technology's performance is important to track because if it is no longer providing a performance benefit it should not be transitioned. Furthermore, if the uncertainty surrounding the technology's performance impact is still large it may not be ready to be transitioned. It was established that the progression of performance and the affect of the remaining uncertainty can be tracked through mean and variance at the technology level. At the portfolio-level, POS or S/N can be used in conjunction with WPV to illustrate the portfolio's performance risk.

The progression of a single technology's readiness risk can be easily observed by using TRL and the number of years until TRL 9 is achieved (or a similar measure of difficulty). Regular updates of the readiness risk enables identification of unfavorable trends. For the progression of the entire portfolio, it was observed that the use of average cardinal TRL and average non-zero years until TRL 9 is achieved provides the best identification of readiness risk trends. Ideal and non-ideal trends were established to enable decision makers to identify how their readiness risk is progressing over time.

Based upon these observations, the process provided in Figure 90 was finalized and Hypothesis 4.1 and Hypothesis 4.2 are partially supported. Recall, Hypothesis 4.1 stated that communication of readiness risk through measures of readiness and difficulty would be sufficient for transition readiness assessments. It was observed that these measures will properly communicate the information. However, it was also established that these measures should be calculated independently for individual technologies and in their aggregate forms for the entire portfolio. Therefore, the final answer to Research Question 4.1 is as follows:

Risk depictions at the technology-level and portfolio-level that communicate the readiness and the remaining expected difficulty provide adequate readiness information to identify technologies with favorable and unfavorable readiness risk trends.

For performance risk, Hypothesis 4.2 stated that communication of the amount of remaining uncertainty and the impact it has on the POS of performance objectives will provide sufficient information for transition assessments. Again, it was observed that it is important to track this information at both the technology-level and the portfolio-level. Furthermore, it was established that tracking the POS at the technology-level is not practical and the S/N measure could be used instead. Finally, at both levels is was determined that the use of WPV communicates how the uncertainty negatively affects the expected performance. Therefore, the final answer to Research Question 4.2 is as follows:

A risk depiction at the technology-level comprised of the mean and variance and a risk depiction at the portfolio-level comprised of the POS and WPV provide adequate performance information to identify technologies with favorable and unfavorable performance risk trends.

CHAPTER VII

METHODOLOGY SYNTHESIS AND IMPLEMENTATION ON CASE STUDY

The results from Experiment Sets 1.0-4.0 provided answers to the relevant Research Questions which enabled the finalization of the QuantUM^3 methodology. Figure 103 provides a final depiction of the QuantUM^3 methodology and where each of the previously presented supporting processes fit.

The QuantUM^3 process begins with *Strategic Planning* where an architecture is selected and key low-level impacts and required capabilities that will enable the performance goals to be met are identified. This includes the identification of potential impact scenarios, which provide pre-determined sets of impacts that enable the objectives to be met. After all steps in *Strategic Planning* have been completed, *Technology Selection* begins. It was established that technology selection is comprised of formulating technology portfolios, evaluating technology portfolios, and selecting a final set of technologies to pursue. A decision then must be made regarding supplemental technologies after the initial technology portfolio is selected. If resources remain, additional technologies can be selected to back-up high risk technologies. If the resources are not available or no high risk technologies have been identified, the next phase of development will begin.

The next development phase, *Technology Experimentation*, involves the planning and execution of experimental plans for the selected technology portfolio. It was established that number of experiments planned at once can vary and it may be done in an iterative manner. When this is the case, both the need for further experimentation and the viability of further experimentation must be re-assessed after each iteration.

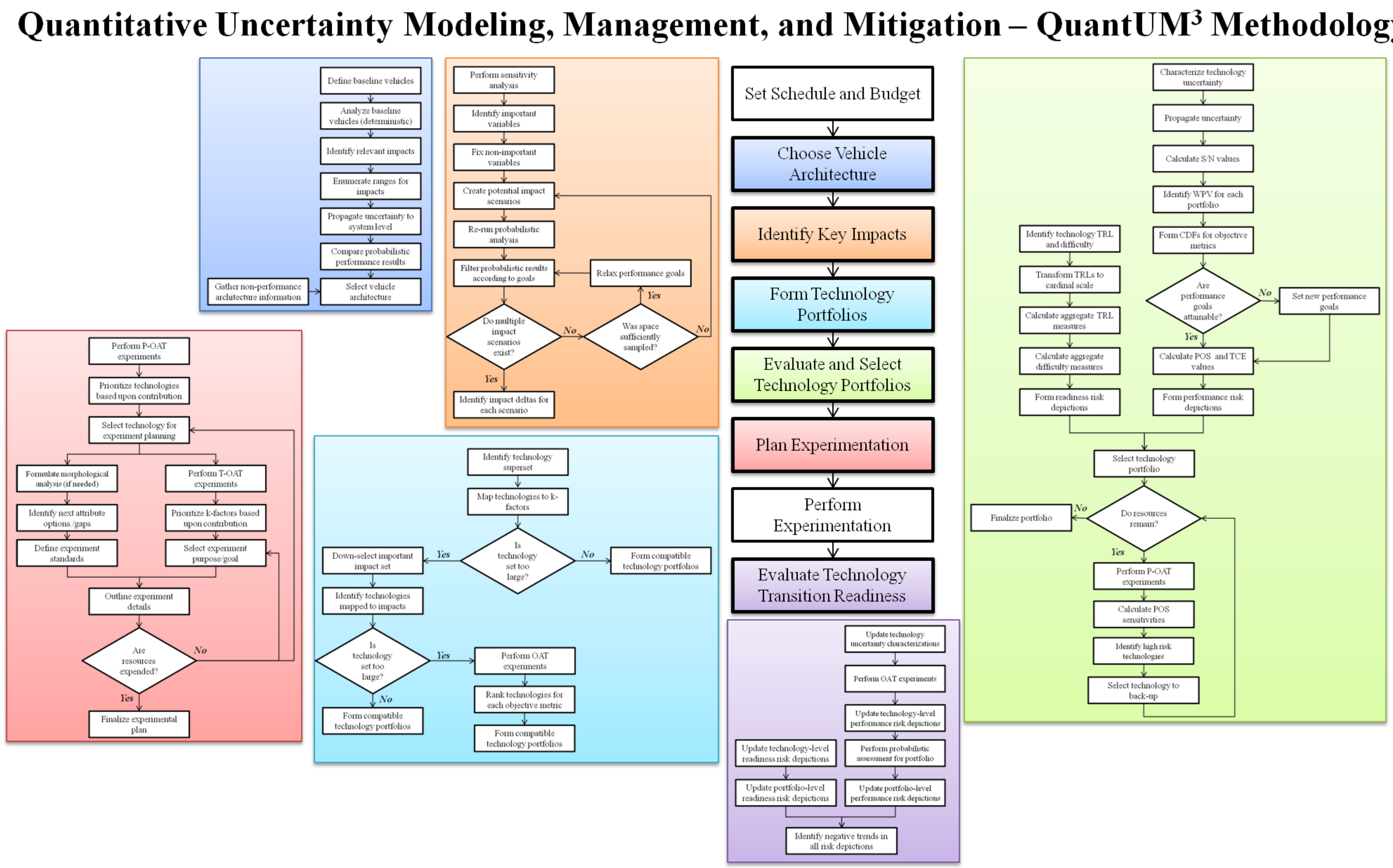

Figure 103: Finalized QuantUM^3 Methodology and all supporting processes.

When it is established that technology experimentation has concluded, the program will transition into the next development phase.

The final phase of development included in this methodology is *Technology Transition Readiness Analysis*. During this phase, the progression of the technologies' performance risk and readiness risk is tracked at the technology-level and the portfolio-level. This enables identification of how the entire portfolio is performing as well as each individual technology. As Figure 33 shows, there are a number of different decision loops that could occur within the transition readiness analysis. First, it must be determined if the technologies under consideration are still considered worthwhile. Their worth is defined by the performance benefit they will provide to the system. If technologies are no longer worthwhile, they are not pursued any further and, if resources remain, new technologies are selected for further development. If the technologies are deemed worthwhile, their readiness is assessed next. If the technologies have an acceptable readiness risk, they are recommended for transition into system development. If the technologies do not have an acceptable level of readiness risk, they must be developed further. If resources remain, new experiments are planned for the technologies. If no resources remain, the development program ends and the technologies will be considered for during a new technology development program.

The final step of this research is to demonstrate the methodology from top to bottom and identify how risk mitigation can be incorporated when an unacceptable risk has been identified. Within this chapter the entire QuantUM^3 methodology is implemented from top to bottom to demonstrate the integrated process. After implementation, the results will be used to demonstrate how risk mitigation can be planned and Hypotheses 5.1 and 5.2 will be addressed.

7.1 Phase 1: Strategic Planning

The same vehicle architectures considered in Chapter 5 were considered for this final implementation. Recall, Table 11 provided the 2010 baseline performance of the LSA vehicle, LTA vehicle, and HWB vehicle with a geared fan engine and Figure 40 provided the results of the probabilistic assessment. It was previously established that there can be many reasons other than performance potential that a vehicle architecture is selected. It was previously demonstrated that a decision scenario that preferences a concept with less design uncertainty and fewer certification issues would result in the selection of the LTA vehicle. Now, however, it is assumed the decision scenario is to have performance potential heavily outweigh other factors. The HWB architecture with the geared fan engine provides the best anticipated performance with respect to all three objective metrics. Therefore, it was selected as the desired system architecture for the technology development program for this implementation.

The 48 factors utilized for the probabilistic forecasting assessment for architecture selection were utilized for the sensitivity analysis. Again two separate sensitivity analyses were performed, a local prediction profiler assessment and a global ANOVA assessment. The results of the local assessment are provided in Figure 104, Figure 105, and Figure 106. As it was discussed in Experiment Set 1, it is observed that the local assessment enables the identification of trends among the k-factors, mid-level metrics, and system objective metrics. For example, it is clear in Figure 104 that FCDSUB, which is a factor for subsonic drag coefficients, and FRFU both have an impact on fuel burn reduction. However, it is difficulty to determine which slope is larger so a quantitative ranking is not enabled. The prediction traces to enable the confirmation that the environment is working correctly, which is important for model validation purposes. It is observed that all noise suppression factors are affecting the noise margin and engine design variables, such as the fan pressure ratio and burner efficiency, are impacting the NOx emissions. Based on these observations, it was determined that the ANNs adequately represent the physics of the EDS environment.

The ANOVA analysis was next conducted and Figure 107 provides the results through a tornado plot for each of the three objective metrics. The impact variables that affect the metrics the most are shown at the top of the tornado plots. Only variables with a significant impact are provided for each objective metric in Figure 107. It is observed that a total of 22 impacts were identified as important for fuel burn reduction, 13 impacts were identified as important for noise margin, and 14 impacts were identified as important for NOx emissions. Comparing these results to those for the LTA vehicle in Figure 49, it is established that many of the same impacts are prioritized for the objective metrics. Therefore, it is expected that many of the same technologies will also be prioritized.

The probabilistic performance were next used to enable the identification of potential impact scenarios. Recall the performance goals set for the NASA ERA program provided in Figure 35 are a 50% fuel burn reduction, 42dB noise margin, and a 75% LTO NOx reduction. It appears that the HWB configuration may enable the noise margin goal to be met but it falls short of the the other two goals. Therefore, the following goals were set: a 45% fuel burn reduction, 42dB noise margin, and a 65% NOx reduction below CAEP 6. The results were filtered with the new performance goals and twelve impact scenarios were identified that meet all three of the goals simultaneously. Figure 108 shows the HWB impact scenarios highlighted in blue. The identified impacg scenarios are further decomposed and explained through the parallel plot shown in Figure 109. The blue line represents the 2010 baseline HWB vehicle to enable an identification of whether positive or negative deltas are required.

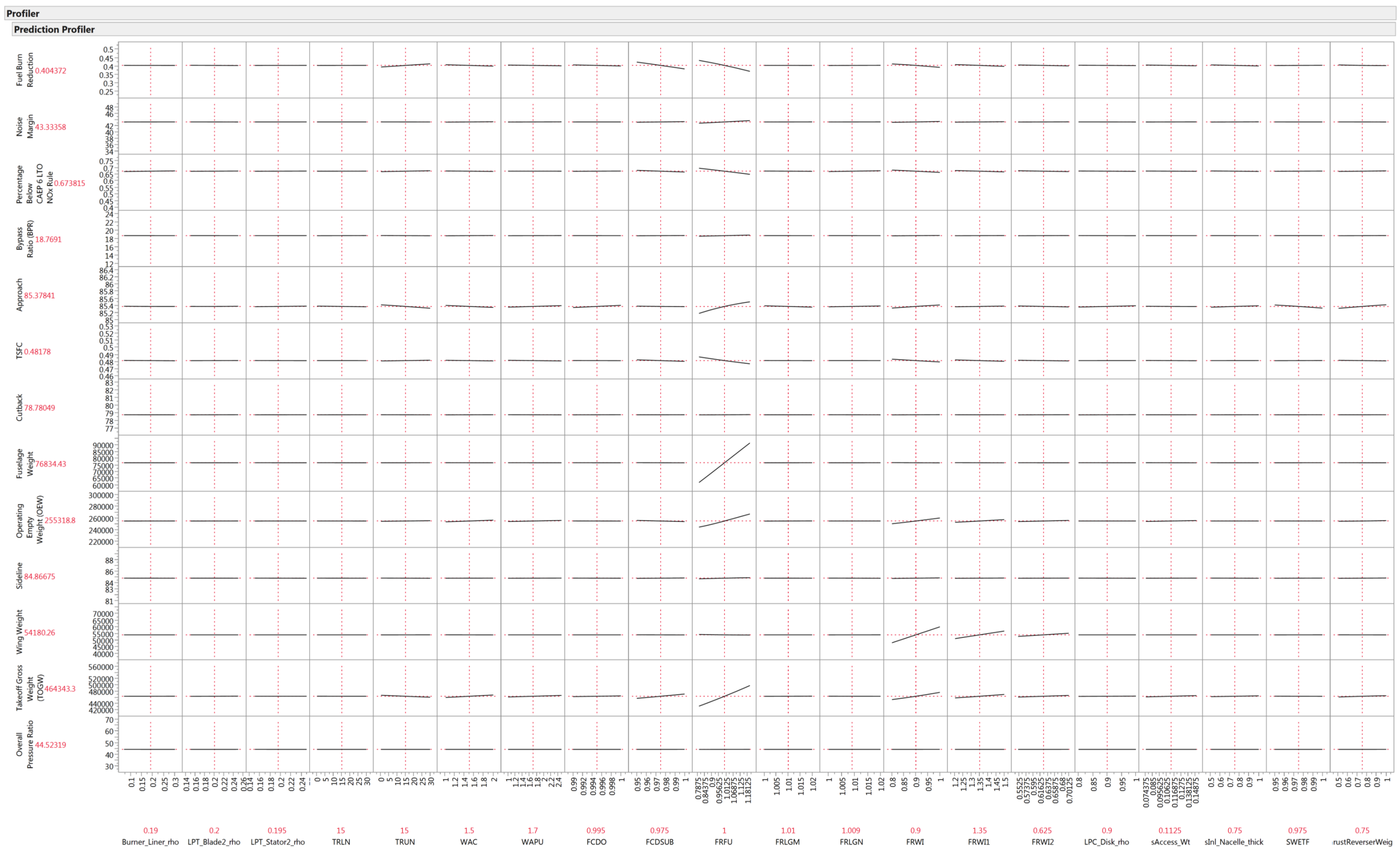

Figure 104: Prediction profiler sensitivity study for HWB vehicle sizing and flowpath variables.

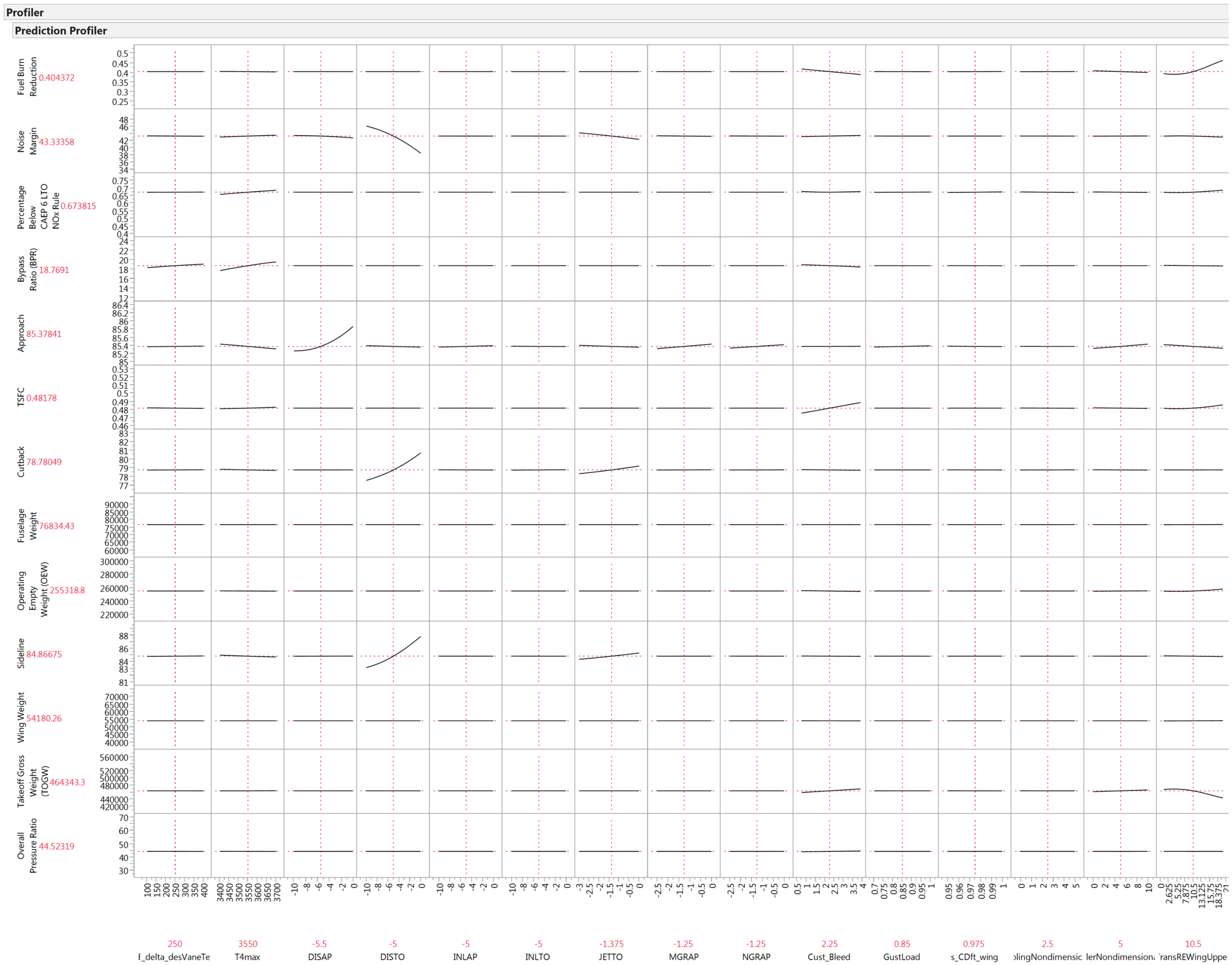

Figure 105: Prediction profiler sensitivity study for HWB engine design variables and noise factors, Part 1.

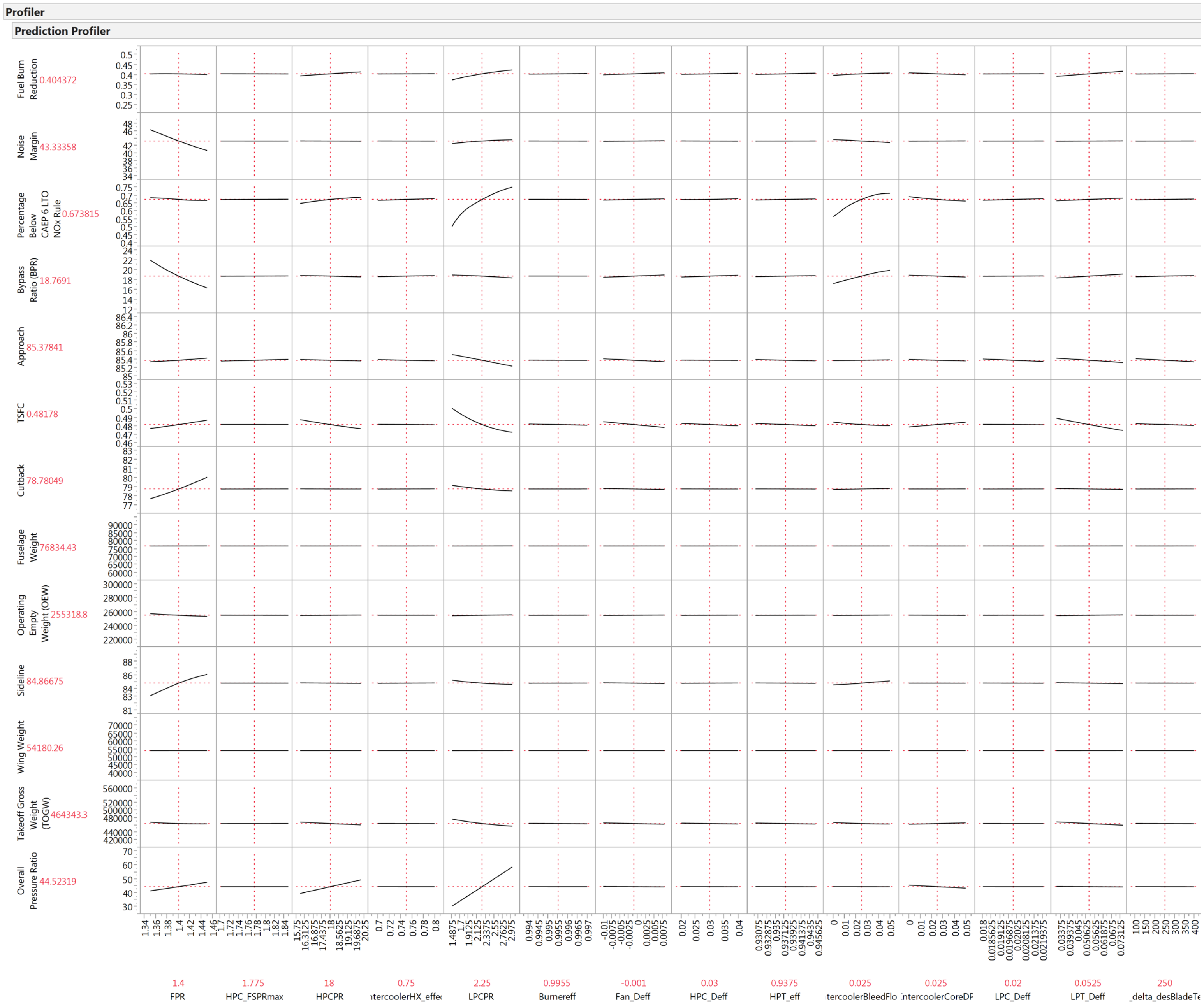

Figure 106: Prediction profiler sensitivity study for HWB engine design variables and noise factors, Part 2.

Screening for Fuel Burn Reduction

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
TransREWingUpper	0.025680	51.31	<.0001*
FRFU	-0.020078	-40.12	<.0001*
LPCPR	0.015635	31.24	<.0001*
FCDSUB	-0.012575	-25.12	<.0001*
Cust_Bleed	-0.009197	-18.37	<.0001*
FRWI	-0.008976	-17.93	<.0001*
TRUN	0.007775	15.53	<.0001*
HPCPR	0.005237	10.46	<.0001*
Fan_Deff	0.004009	8.01	<.0001*
FRWI1	-0.003033	-6.06	<.0001*
HPC_Deff	0.002944	5.88	<.0001*
ThrustReverserWeight	-0.002517	-5.03	<.0001*
WAPU	-0.002092	-4.18	0.0002*
sInl_Nacelle_thick	-0.001982	-3.96	0.0004*
HPT_eff	0.001885	3.77	0.0005*
FCDO	-0.001809	-3.62	0.0006*
FRWI2	-0.001316	-2.63	0.0099*
WAC	-0.001303	-2.60	0.0106*
TRLN	-0.001056	-2.11	0.0385*
IntercoolerNondimensionalWeight	-0.001086	-2.17	0.0334*
T4max	0.000901	1.80	0.0747
FPR	0.000849	1.70	0.0921

Screening for Noise Margin

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
DISTO	-2.32520	-158.84	<.0001*
FPR	-1.48079	-101.16	<.0001*
JETTO	-0.61189	-41.80	<.0001*
LPCPR	0.35522	24.27	<.0001*
FRFU	0.24367	16.65	<.0001*
DISAP	-0.18736	-12.80	<.0001*
FRWI	0.05701	3.89	<.0001*
Fan_Deff	0.05985	4.09	<.0001*
MGRAP	-0.05184	-3.54	0.0009*
INLAP	-0.04570	-3.12	0.0023*
FCDSUB	0.04027	2.75	0.0062*
FRWI1	0.04068	2.78	0.0058*
FRWI2	0.02816	1.92	0.0549

Screening for Percentage Below CAEP 6 LTO NOx Rule

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value
IntercoolerBleedFlow	0.043299	96.31	<.0001*
LPCPR	0.015151	33.70	<.0001*
FPR	-0.013288	-29.56	<.0001*
T4max	0.010222	22.74	<.0001*
IntercoolerCoreDP	-0.009240	-20.55	<.0001*
LPT_Deff	0.004983	11.08	<.0001*
HPC_Deff	0.003659	8.14	<.0001*
IntercoolerHX_effect	0.003247	7.22	<.0001*
Burnereff	-0.002441	-5.43	<.0001*
HPCPR	-0.002453	-5.46	<.0001*
Burner_Liner_rho	0.001590	3.54	0.0007*
IntercoolerNondimensionalWeight	0.001192	2.65	0.0090*
LPT_delta_desVaneTemp	0.000921	2.05	0.0406*
HPC_FSPRmax	0.000775	1.72	0.0843

Figure 107: ANOVA results for fuel burn reduction, noise margin, and NOx emissions.

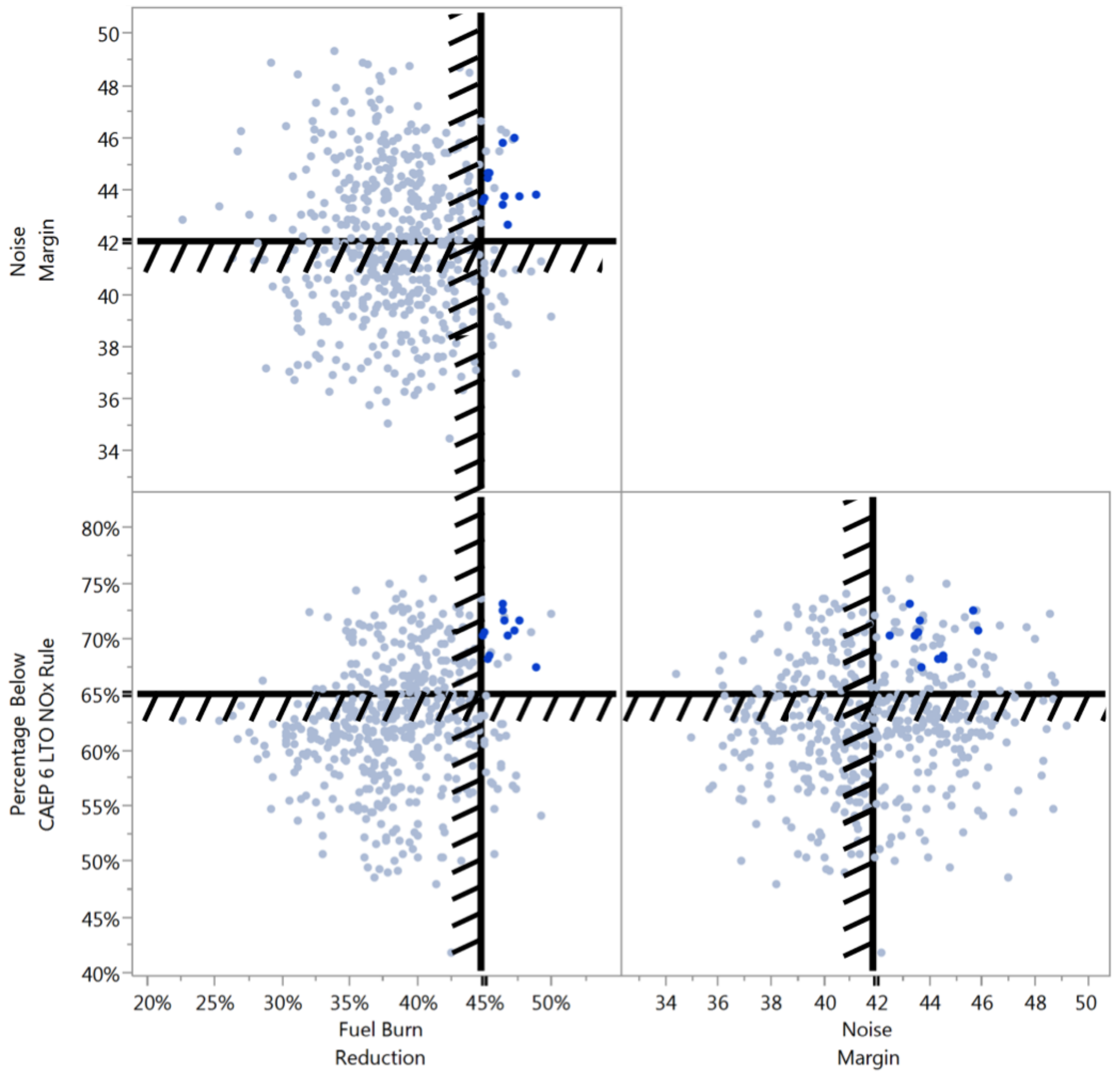

Figure 108: HWB impact scenarios from TIF probabilistic results.

The details of the impact scenarios presented in Figure 109 identify that a simultaneous decrease in approach, cutback, and sideline noise is required to meet the noise margin goal. Furthermore, A decrease in wing weight, OEW, and TOGW is required for all scenarios. It is also observed that all scenarios accept one require a decrease in fuselage weight. The engine's OPR abd BPR must increase from the baseline value and the TSFC must decrease in order to achieve the goals simultaneously.

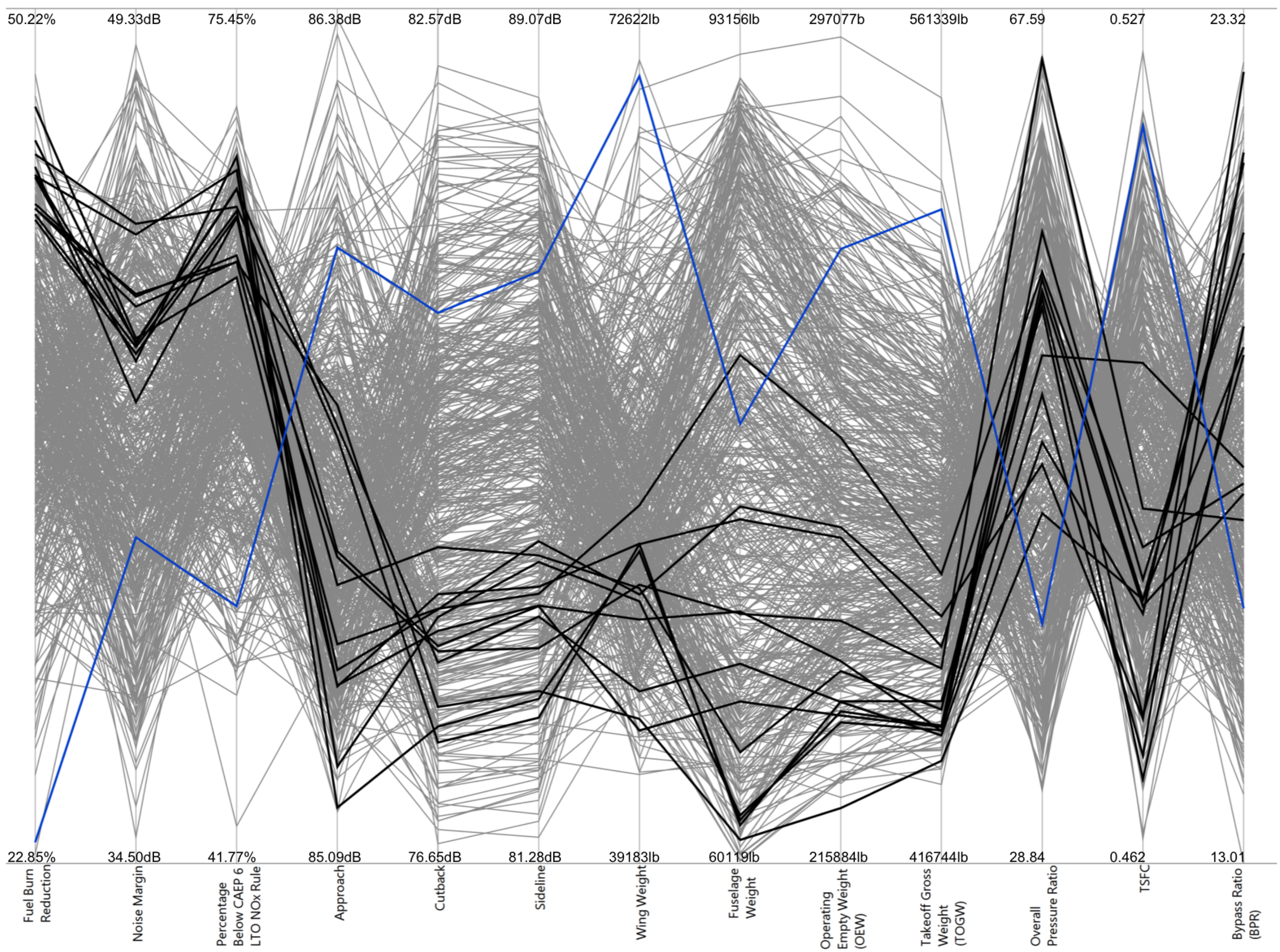

Figure 109: Parallel plot of mid-level metrics for HWB impact scenarios.

7.2 Phase 2: Technology Selection

The first step of *Technology Selection* is *Formulate Technology Portfolios.* First, the technology superset must be determined and the capabilities the technologies will provide must be mapped to the identified k-factors. Next, it must be determined if the number of technologies in the superset is too large to generate all potential technology portfolios. If the superset is not too large, all possible technology portfolios are generated and technology portfolio formulation is complete.

If the number is too large, the technologies must be prioritized. First, the technologies are prioritized based upon how they map the important impacts identified in Phase 1. The important impacts can be selected strictly based upon the sensitivity analysis or by the way they are grouped in defined impact scenarios. After this level of prioritization is complete, the number of technologies under consideration is re-assessed. If the reduced set is now at an acceptable number, all possible technology portfolios are generated and this step is completed. If the number is still too large, a second layer of prioritization is conducted through the use of OAT experiments for the technologies. The OAT experiments enable the identification of how technologies affect the objective metrics on an individual basis. Technologies that provide a large benefit to one or more of the objective metrics can be identified and prioritized for inclusion in technologies portfolios. The information provided by both layers of prioritization is then used together to reduce the number of technologies under consideration to an acceptable number and compatible technology portfolios are generated.

The technologies provided in Appendix A were considered for the HWB configuration. Technologies were mapped to the impact variables identified as important for each of the objective metrics from the ANOVA assessment conducted during Phase 1. The technology mappings are provided in Table 32 for fuel burn reduction, Table 31 for noise margin, and Table 33 for NOx emissions. The tables provide both the variable and its corresponding technologies. This prioritization resulted in 47 technologies, which is a large reduction from 88. However, further prioritization was desired.

The OAT experiments were performed for each of the technologies on the 2010 baseline HWB model. Triangular probability distributions were assumed for the k-factors of each technology and the uncertainty was propagated utilizing 50,000 case Monte Carlo analyses on ANNs. Performance deltas were calculated for each technology by subtracting the 2010 HWB baseline objective value from the mean value of the OAT experiment. The top 10 technologies and their performance deltas are provided in Table 34 for fuel burn reduction, Table 35 for noise margin, and Table 36 for NOx emissions.

Table 31: Key impacts for noise margin and their corresponding technologies

Factor	Technologies
DISTO	T56, T40, T49, T42, T57, T41
FPR	None
JETTO	T47
LPCPR	T22.1, T26.1
FRFU	T3.1, T78.2, T79.2, T80.2, T81.2, T82.2, T83.2, T84.2
DISAP	T40, T56, T57, T41
FRWI	T3.2, T78.1, T79.1, T81.1, T82.1
Fan_ Deff	None
MGRAP	T16.1
INLAP	T41, T52, T54, T42, T53, T57
FCDSUB	None
FRWI1	T80.1, T83.1, T84.1
FRWI2	T80.1, T83.1, T84.1

Table 32: Key impacts for fuel burn reduction and their corresponding technologies

Factor	Technologies
TransREWingUpper	T10.1, T11.1, T69.1
FRFU	T3.1, T78.2, T79.2, T80.2, T81.2, T82.2, T83.2, T84.2
LPCPR	T22.1, T26.1
FCDSUB	None
Cust_ Bleed	None
FRWI	T3.2, T78.1, T79.1, T81.1, T82.1
TRUN	T11.3
HPCPR	T32.B
Fan_ Deff	None
FRWI1	T80.1, T83.1, T84.1
HPC_ Deff	T20, T67
ThrustReverserWeight	None
WAPU	T7
sInl_ Nacelle_ thick	T72
HPT_ eff	T23, T67
FCDO	T72
FRWI2	T80.1, T83.1, T84.1
WAC	T73, T10.1, T10.2
TRLN	None
IntercoolerNondimensionalWeight	T22.1
T4max	None
FPR	None

Table 33: Key impacts for NOx emissions and their corresponding technologies

Factor	Technologies
IntercoolerBleedFlow	T22.1
LPCPR	T22.1, T26.1
FPR	None
T4max	None
IntercoolerCoreDP	T22.1
LPT_ Deff	T33.2, T33.1, T67
HPC_ Deff	T20, T67, T32.B
IntercoolerHX_ effect	T22.1
Burnereff	T62+T61
HPCPR	T32.B
Burner_ Liner_ rho	T63
IntercoolerNondimensionalWeight	T22.1
LPT_ delta_ desVaneTemp	T27.4B, T28.4, T29.3+T31, T27.4C
HPC_ FSPRmax	None

Table 34: Key technologies for fuel burn reduction from OAT experiments

Technology	Performance Delta
T69.1	10.39%
T10.1	8.42%
T11.3	3.43%
T11.1	3.12%
T3.1	2.74%
T80.2	2.73%
T84.2	2.72%
T22.1	2.29%
T3.2	2.16%
T32.B	2.12%

Table 35: Key technologies for noise margin from OAT experiments

Technology	Performance Delta
T41	2.135
T42	1.765
T40	1.643
T57	1.145
T56	0.95
T47	0.782
T76	0.523
T26.1	0.27
T83.3	0.268
T83.1	0.164

Table 36: Key technologies for NOx emissions from OAT experiments

Technology	Performance Delta
T22.1	13.50%
T20	2.86%
T29.1+T31	1.47%
T24.B	1.17%
T25	0.96%
T67	0.78%
T29.3+T31	0.77%
T7	0.76%
T93.2	0.74%
T21	0.72%

The 47 technologies from the first phase of prioritization that also were identified by the OAT experiments were down-selected for technology portfolio formulation. Fifty different compatible technology portfolios of eight technologies each were generated from this final set and utilized for *Technology Portfolio Evaluation and Selection*. For readiness risk, the TRL and difficulty values are assigned to each individual technology. The TRL values must then be transformed into the cardinal TRL scale provided in Table 5. Next, aggregate values of TRL and difficulty are calculated for each technology portfolio under evaluation. The resulting values are then plotted to form the readiness risk depictions. It was established in Chapter Six and Chapter Seven that the readiness risk depictions are comprised of the average TRL and the average number of years until TRL 9 is achieved. Figure 110 provides the resulting readiness risk assessment for each of the 50 technology portfolios under consideration. Recall, the bottom right corner provides the least amount of readiness risk and the top left provides the most.

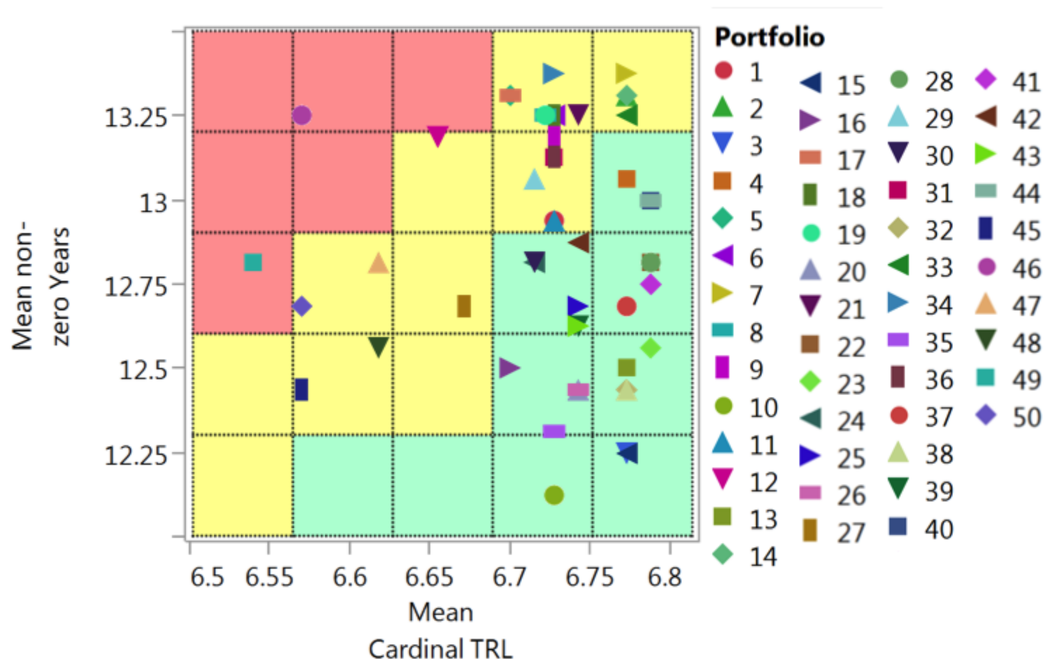

Figure 110: Readiness risk assessment for 50 technology portfolios under consideration.

For performance risk, the first step is to characterize the technology level uncertainty. Next, the uncertainty for each portfolio is propagated to the objective metrics and the S/N and WPV are calculated from the probabilistic results. CDFs for each objective metric are then formulated and the previously set goals are re-evaluated. If the goals are not likely achievable by any of the technology portfolios under consideration, relaxed performance goals are set. Next, the POS values for each objective metric are calculated for each technology portfolio. Finally, the S/N, POS, TCE, and WPV measures are used to formulate the performance risk depictions.

For the case study, triangular distributions were used to depict the technology uncertainty. After the uncertainty was propagated, it was determined that no relaxation of the previously established goals were required, which is demonstrated through Figure 111. Figure 111 shows that the mean performance for each of the fifty technology portfolios under consideration are within the TIF probabilistic assessment results conducted previously.

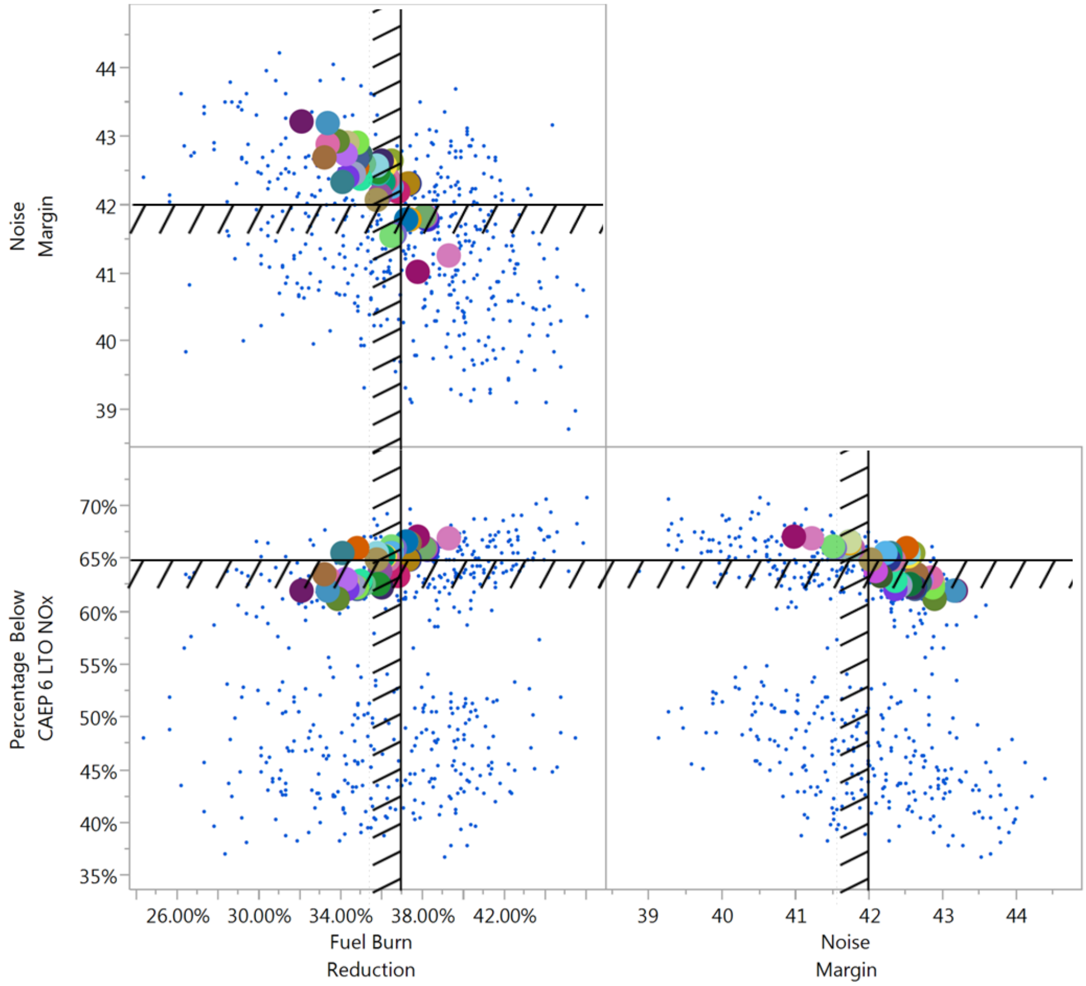

Figure 111: Comparison of mean performance of the 50 technology portfolios to the TIF probabilistic assessment.

The resulting performance risk depictions are provided in Figure 112 for fuel burn reduction, Figure 113 for noise margin, and Figure 114 for NOx emissions. Recall, the top right corner is the area with the least amount of performance risk and the bottom left is the area with the most. It is observed that no portfolios provide a 100% POS for any of the goals, but there are many that provide a high POS.

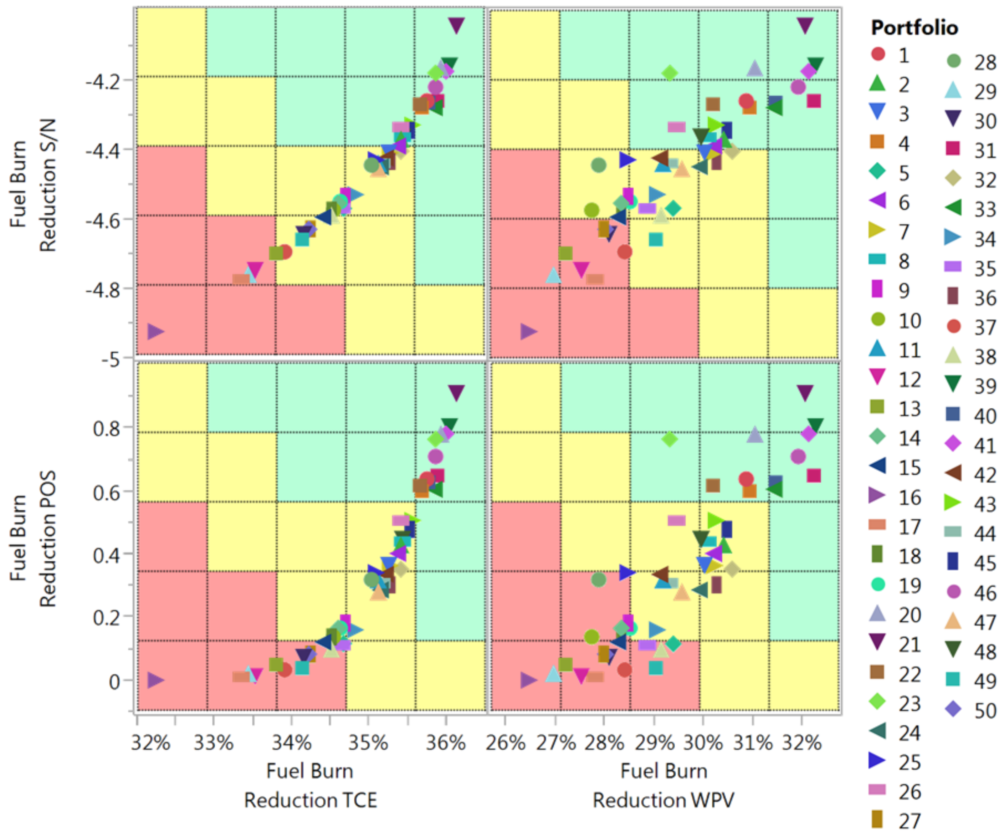

Figure 112: Fuel burn reduction performance risk assessment for 50 technology portfolios under consideration.

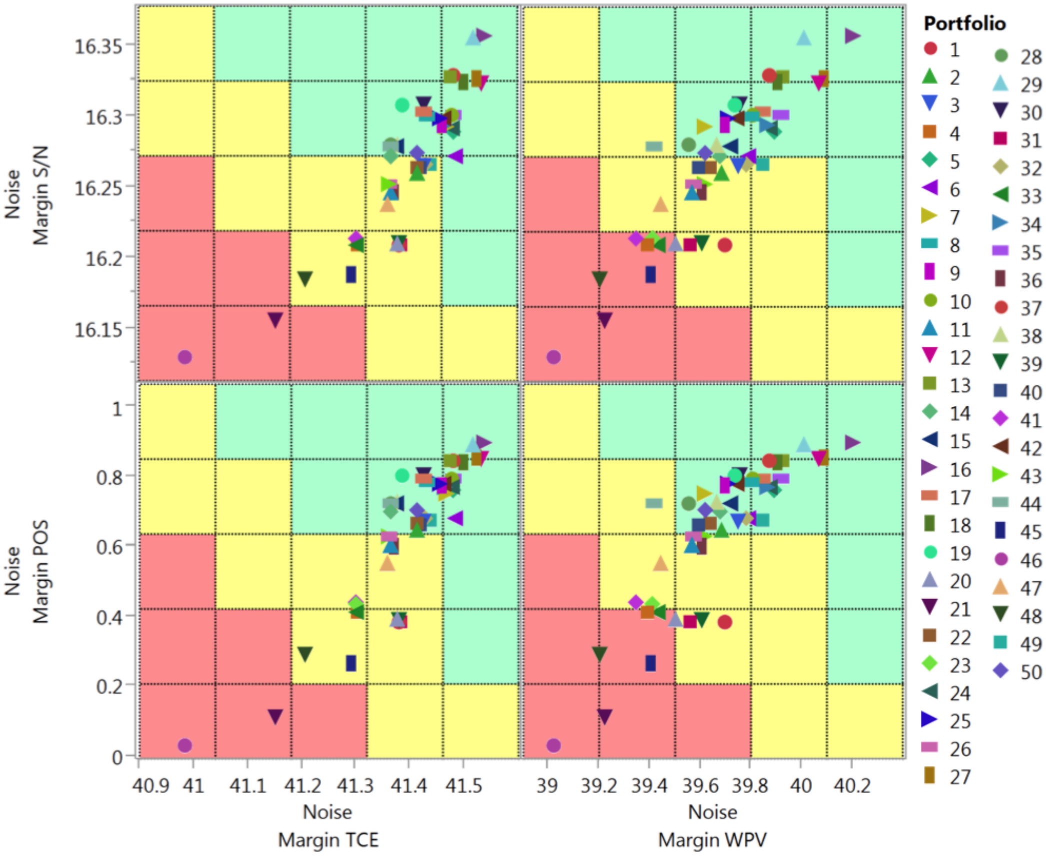

Figure 113: Noise margin performance risk assessment for 50 technology portfolios under consideration.

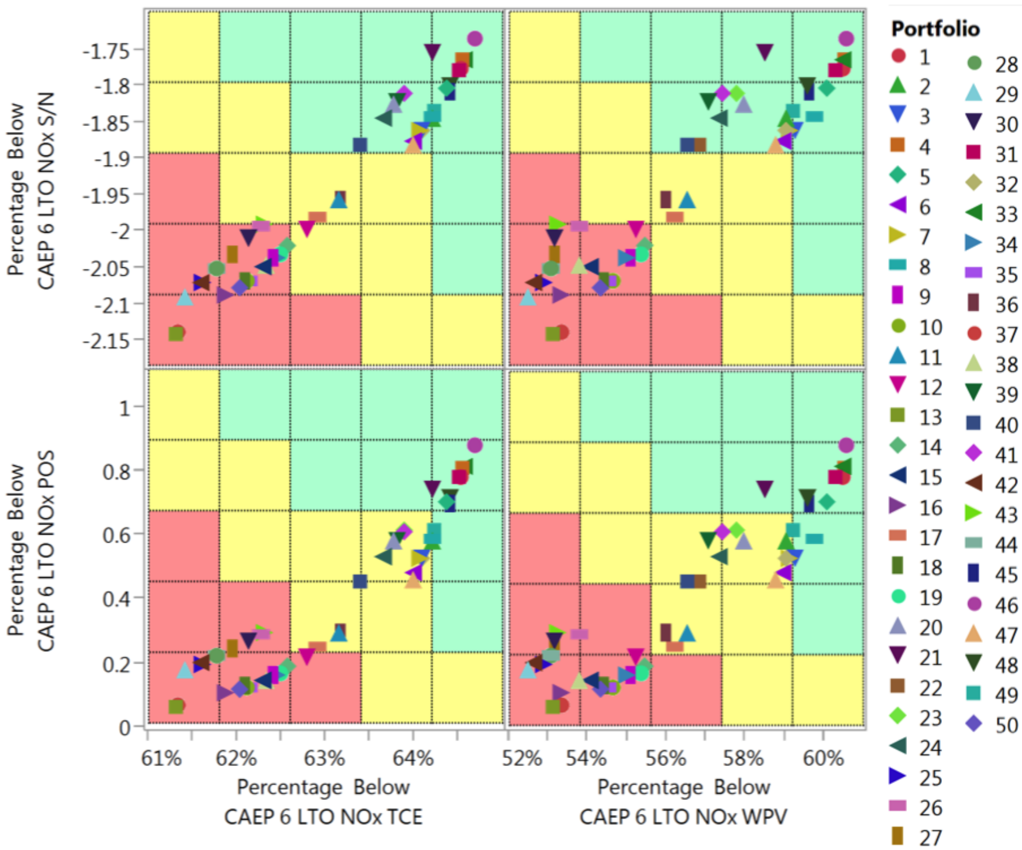

Figure 114: NOx emissions performance risk assessment for 50 technology portfolios under consideration.

The next step of the process is to down-select a technology portfolio. It was outside the scope of this research to recommend a decision making approach for technology development. However, the TOPSIS decision making process was utilized for the case study to identify a favorable technology portfolio. The decision scenario assumed was one where the objective is to select a portfolio that has both low performance risk and low readiness risk.

TOPSIS was implemented once for readiness risk and once for performance risk to obtain rankings of the technology portfolios. For readiness risk, the TRL and difficulty were equally weighted for the calculation of the ideal distance. For performance risk, POS was used as the measure of likelihood and WPV was used as the measure of consequence. The likelihood and consequence measures for each of three objective metrics were all equally weighted for calculation of the ideal distance. Next, the rankings created by the distance calculations were compared to identify a suitable portfolio. Figure 115 provides a visual comparison of the results through the use of a parallel plot. The TOPSIS performance risk results are on the left side of the plot and the TOPSIS readiness risk results are on the right side of the plot. Each line represents a technology portfolio and connects the porftolios TOPSIS performance results to its TOPSIS readiness results. Therefore, a favorable portfolio would be one whose line connects two points towards the top of the plot. This plot enabled the identification of Portfolio 20, as shown on the right side of Figure 115. Therefore, Portfolio 20 was selected for further development.

The final part of *Evaluate and Select Technology Portfolios* is to identify any supplemental technologies that may be selected for development. For prioritization based upon readiness risk, a new risk depiction is developed where the readiness risk of each technology within the selected portfolio is assessed to enable the identification of high priority technologies. The technology-level readiness risk depiction for the case study is shown in Figure 116. From this depiction, T22.1 and T41 have the highest risk and T80.2 has the lowest.

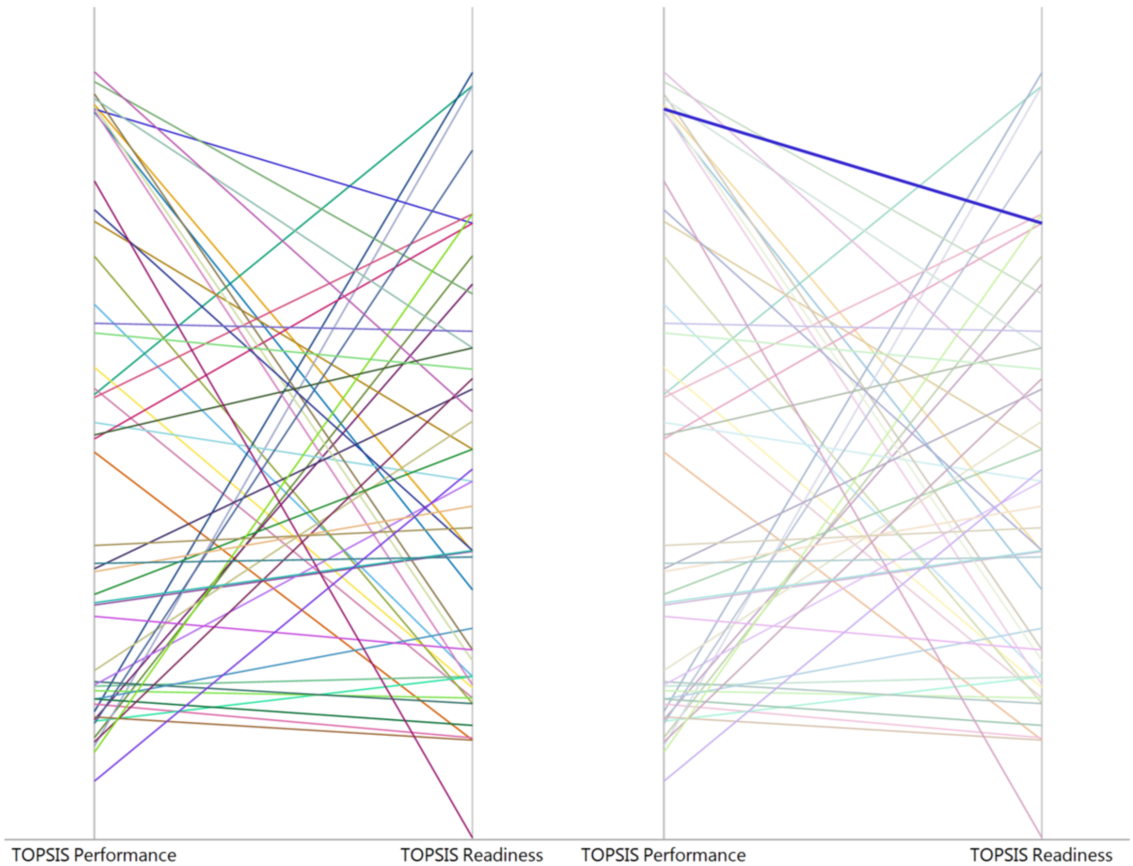

Figure 115: Parallel plot comparing the TOPSIS analyses of readiness risk and performance risk for the 50 technology portfolios under consideration.

For performance risk, the P-OAT experiments are performed. The results of the P-OAT experiments enable the calculation of the POS sensitivity waterfall charts, which in turn enables the identification of high priority technologies. After high priority readiness risk and performance risk technologies have been identified, the availability of resources is assessed. If resources are available, a technology from the portfolio is selected for to be backed-up by a supplemental technology. The supplemental technology is determined based upon the impact variables it is mapped to or its expected performance from the OAT experiments.

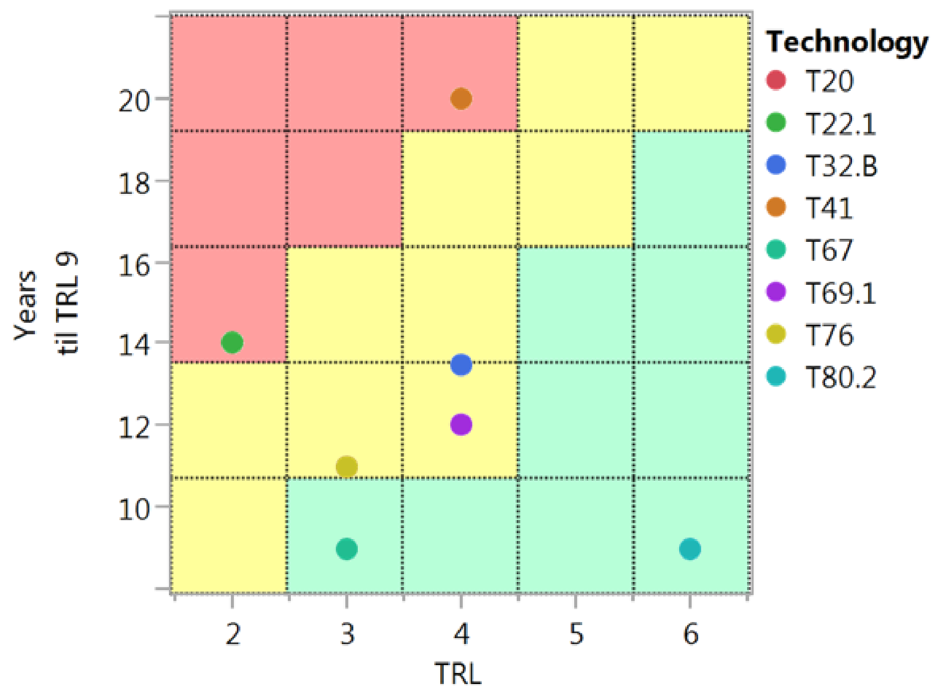

Figure 116: Technology-level readiness risk depiction for technologies in Portfolio 20.

For the case study, the results of the P-OAT experiments are provided by the POS waterfall charts in Figure 117. It is clearly identified from these waterfalls that the engine performance technologies drive the NOx POS, especially T22.1. It is also noticeable that T69.1 drives the fuel burn POS the most with T80.2 and the engine performance technologies also providing positive performance contributions. For noise margin, the two noise technologies, T41 and T76, overwhelmingly drive the performance in a positive direction. Furthermore, it is clearly identified that T69.1, T80.2, and T22.1 negatively impact the noise margin POS.

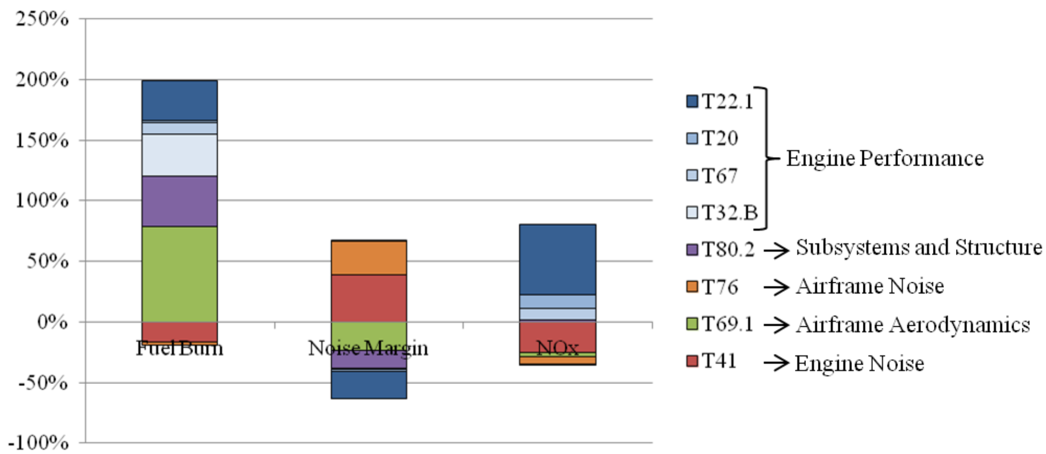

Figure 117: Sensitivity of fuel burn reduction POS and NOx emissions POS to each technology in Portfolio 20.

Based upon the readiness and performance results, T22.1 was first selected to be backed up and T41 was selected second. Identification of the supplemental technologies was done by observing the OAT results shown in Table 36 for T22.1 since it drives NOx performance and Table 35 for T41 since it drives noise margin performance. For T22.1, T24.B was selected as a supplemental technology because it showed a favorable NOx impact and was compatible with all technologies in the portfolio. Likewise, T42 was selected as a supplemental technology for T41 because of its strong expected noise impact.

7.3 Phase 3: Technology Experimentation

The first step in *Plan Experimentation* is to prioritize the technologies, which is done through the P-OAT experiment results for performance. Once a technology, or several technologies, are selected for experimentation their individual readiness and performance must be re-assessed. For readiness, the morphological readiness analysis must be formulated or updated for the technology under consideration. This will enable the identification of what type of experimentation is required to further the TRL through experiment standards. For readiness, the T-OAT experiments are performed to identify where the technology uncertainty sources that have the largest impact on the overall uncertainty. This enables the identification of the experiment goal and the required measurements.

Next, the information provided through the morphological analysis for the experiment standards and the information resulting from the performance assessment that establishes the experiment goal are synthesized to outline the experiment as a whole. At this time, SMEs can use the experiment outline to guide their detailed design of the experimentation. After the experimental plan is defined, the program can assess whether resources exist to plan more experimentation. If more resources do exist, the experimental plan can be augmented in two different ways. First, the individual experiment can be altered to include multiple goals, which would require additional measurements to be taken. Second, a new experiment can be planned for a different technology. Finally, once the resources have been expended the experimental plan is finalized.

The POS contribution results from the P-OAT analysis were presented previously through the waterfall charts in Figure 117. The variance contributions were also calculated and are provided in Figure 118 through separate waterfall charts. The results of both sets of waterfall charts are synthesized through the risk depictions in Figure 119. Technologies that the drive both the POS, in either a negative or positive way, and variance should be prioritized for experimentation. This corresponds to T69.1 for fuel burn reduction, T41 for noise margin, and T22.1 for NOx emissions.

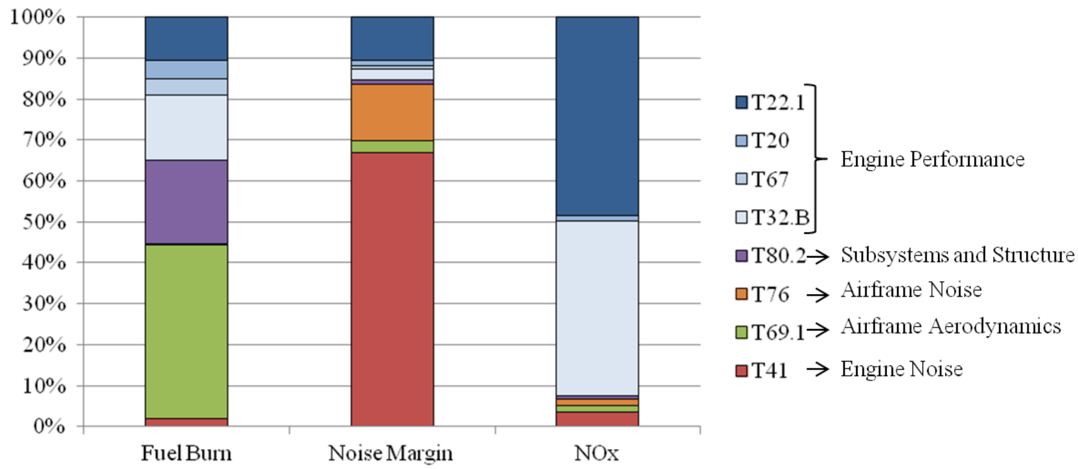

Figure 118: Sensitivity of objective metrics' variance to each technology in Portfolio 20.

Figure 116 provides the individual readiness risk assessments for each technology in Portfolio 20. Technologies in the top left corner have the highest readiness risk and those in the bottom right corner have the lowest. Therefore, T22.1 and T41 have the highest readiness risk out of the eight and T80.2 has the lowest. Therefore, while T22.1 and T41 have both high readiness risk and high performance risk. This led to the prioritization of T41 for experimentation.

T-OAT experiments were next performed to start the experiment planning process. Figure 120 provides the T-OAT results for six of the eight technologies in Portfolio 20. T69.1 and T80.2 are not included in Figure 120 because they are each only mapped to one impact variable and therefore all of their contribution comes from that single variable. For T41, it is clear that ABTC drives the variance for fuel burn and NOx emissions and DISTO drives the variance for noise margin. Recall, T41 was selected because of its contribution to the variance and POS of noise margin. Therefore, it was decided that the experiment should focus on quantifying DISAP, which is a fan discharge noise factor.

The morphological analysis was next consulted to determine the experimental

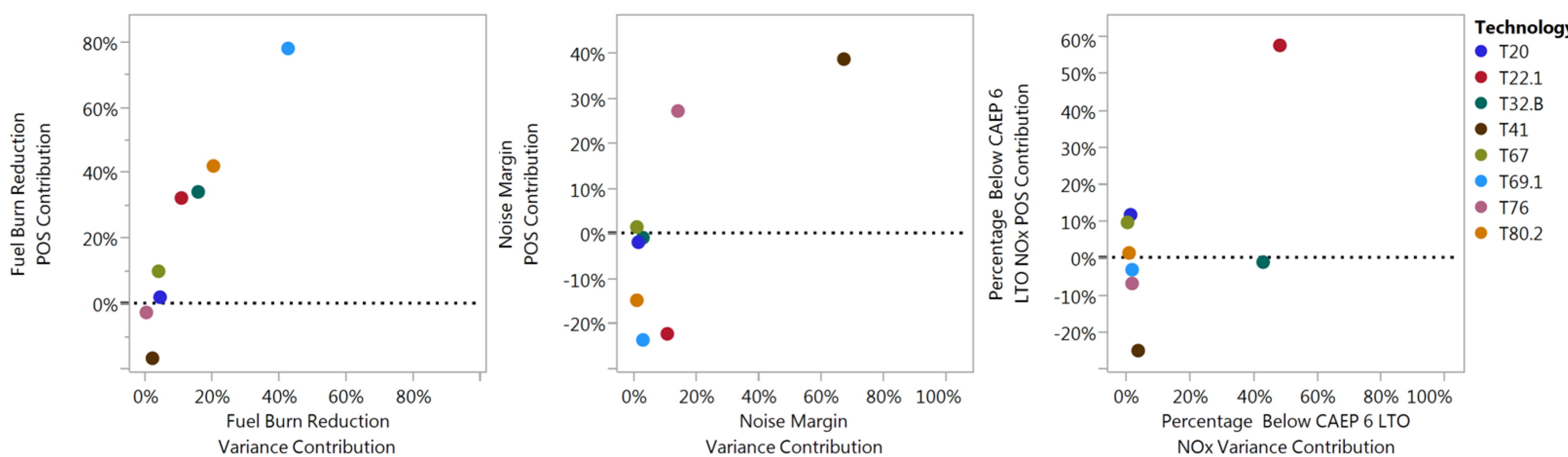

Figure 119: Contribution of each technology to the POS and variance of each objective metric.

standards. T41 is currently at a TRL of 4, therefore the experiment standards should be set by the TRL 5 requirements. As shown in Figure 78, when going from TRL 4 to TRL 5 the fidelity of both the test environment and test article are increased and the level of the test article is increased. Therefore, the desired experiment standards are a controlled, lab environment test of a sub-scale, single sub-system prototype that is semi-functional.

7.4 Phase 4: Technology Transition Readiness Assessment

Transition readiness is a function of the readiness risk and the performance risk of the individual technologies and the portfolio as a whole. For readiness risk, the technology-level readiness risks are updated after all experimentation has been performed and then the portfolio readiness risk is re-evaluated. For performance risk, the technology uncertainty depictions are updated after each experiment is performed. The OAT experiments are conducted again to provide an update of how the independent capabilities provided by the technologies are progressing. The probabilistic assessment for the entire portfolio is also conducted again. Risk depictions for each technology and the portfolio as a whole then updated.

For the case study, it is assumed that enough resources existed to mature each of the technologies within Portfolio 20 and partially mature the supplemental technologies, T24B and T41. Figure 122 shows the progression of readiness risk for the portfolio over the course of the development program. The trend shows a gradual reduction in readiness risk because the mean TRL of the non-baseline technologies steadily increases as the mean number of years until TRL 9 is achieved decreases. The mean TRL is approximately 3.25, which would be too low for transition into system development. However, recall a 3.25 on the cardinal TRL scale is between a 6 and 7 on the ordinal TRL scale. Therefore, it would appear that all technologies are are showing favorable readiness risk reduction trends.

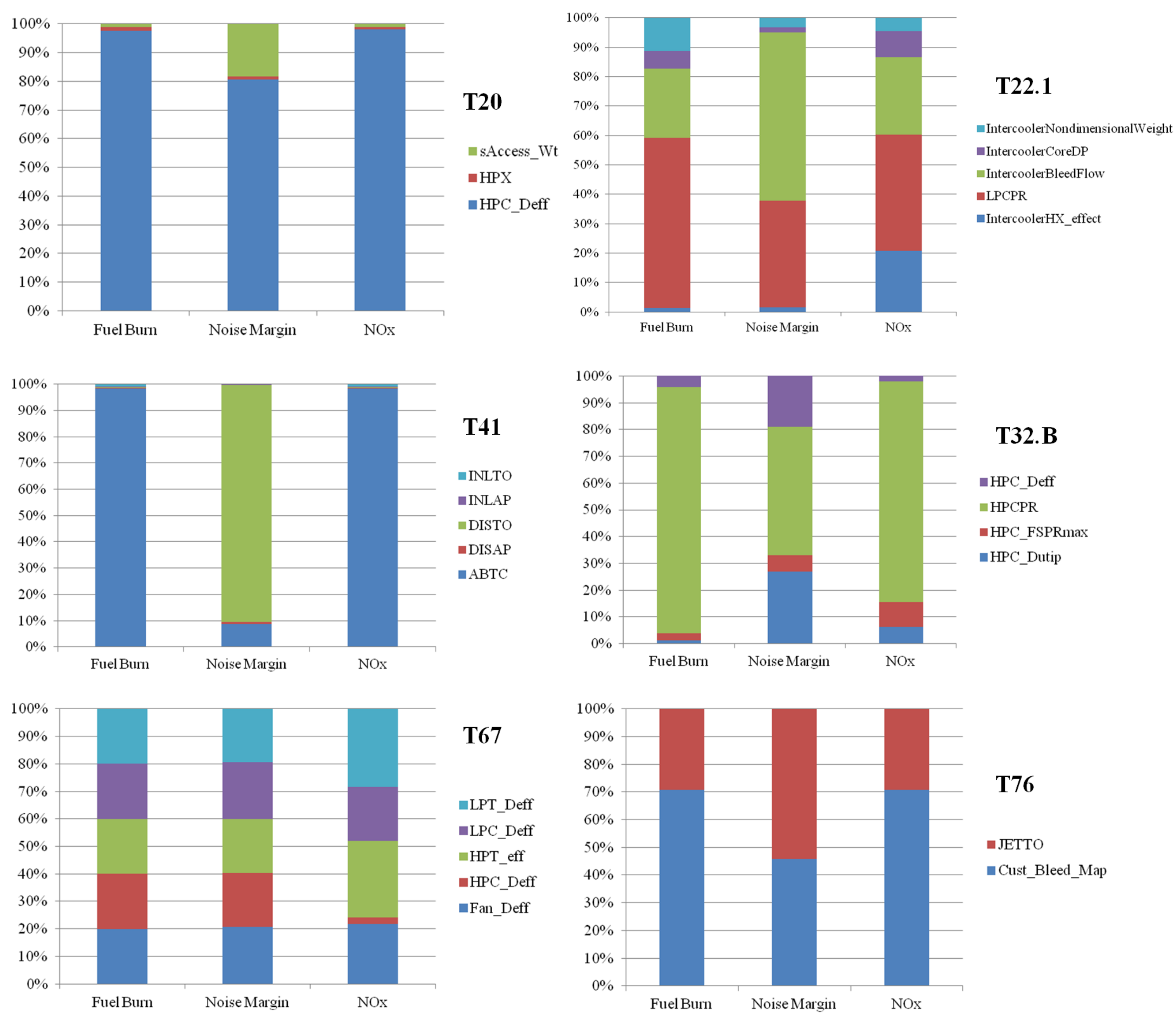

Figure 120: Variance contribution waterfall charts that result from T-OAT experiments for each technology.

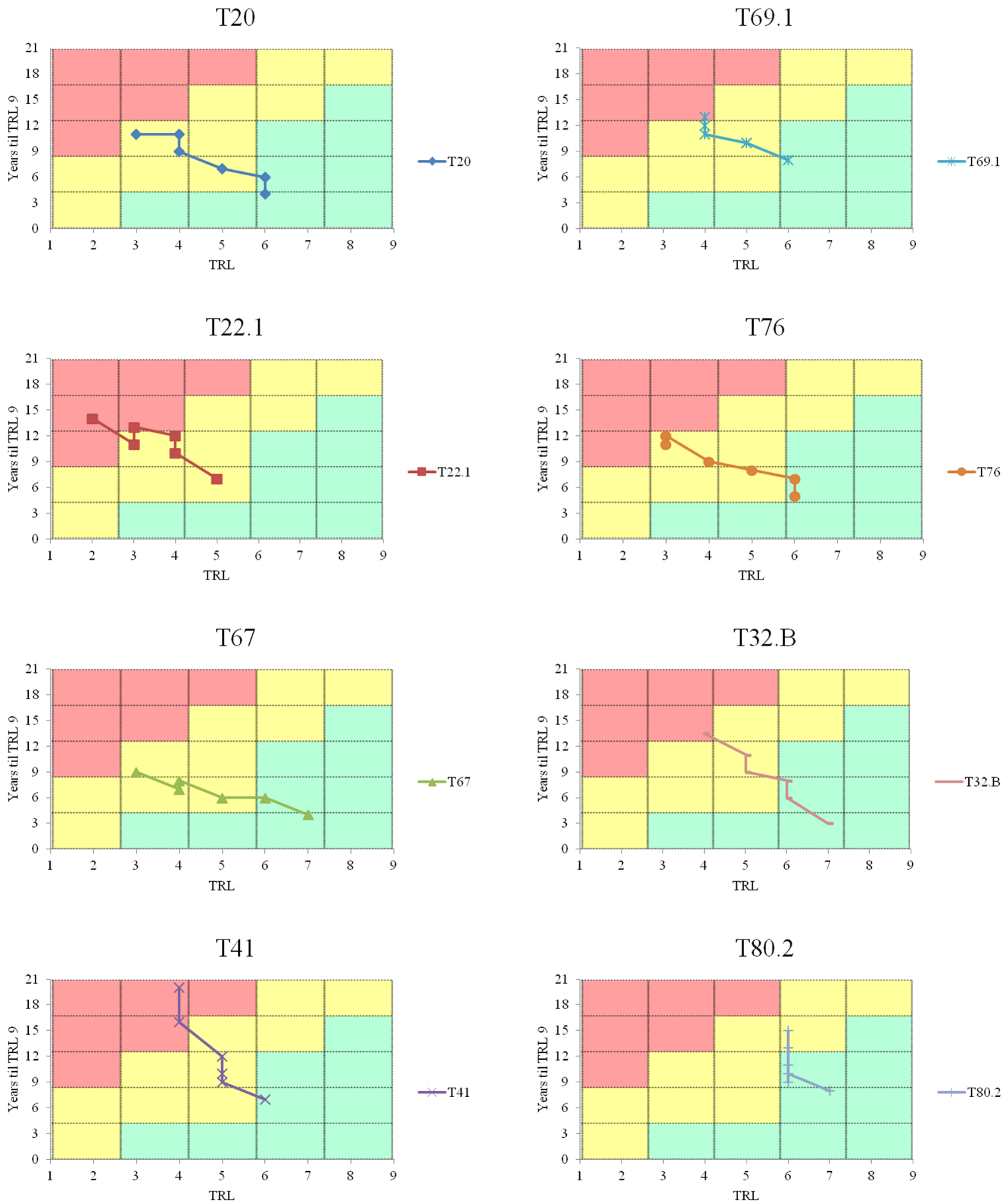

Figure 121: Progression of readiness risk for each technology within Portfolio 20.

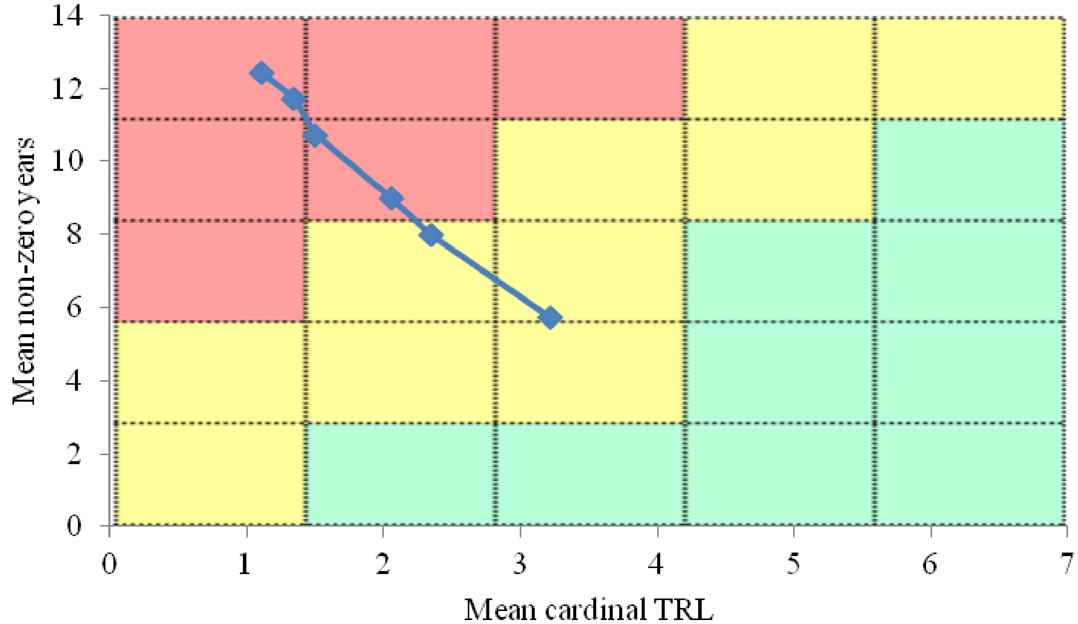

Figure 122: Progression of readiness risk for Portfolio 20.

Figure 121 provides the individual readiness risk reduction trends for each of the technologies in Portfolio 20. T69.1 experiences increasesd readiness risk at first, as the number of years increases from 12 to 13 while the TRL remains at 4. However, it eventually reduces down to 11 years and then both the TRL and number of years progress in a favorable direction. The readiness risk for T22.1 begins to reduce and then increases at TRL 3. However, it recovers and continues to decrease as it moves to TRL 5. T67 experiences a similar increase in readinss when it reaches TRL 4, but it too decreases as it progresses to TRL 5, 6, and 7. For T80.2, The readiness risk increases from the beginning because the number of years increases from 9 to 13 to 15 while remaining at TRL 6. The readiness risk does eventually decrease as the number of years decreases and the TRL increases to 7.

All remaining technologies experience a continuously decreasing readiness risk. The impact of the technologies that experienced areas of increased readiness risk is overshadowed by the technologies that experienced continuously decreasing readiness risk. This reinforces the previously made observation that it is important to track readiness risk at both levels, the technology-level and the portfolio-level. Tracking readiness risk at the technology-level allows decision makers to identify high risk technologies while tracking at the portfolio-level allows them to determine if the risk is equalized across the portfolio.

Next, the performance risk was assessed for each technology and the portfolio as a whole. As previously stated, it was assumed that the final experimental plan included multiple experiments for each technology. Therefore, each technology experienced a decrease in performance uncertainty. Five different updates occurred to the uncertainty and the progression of the portfolio-level performance risk is shown in Figure 123 for fuel burn reduction, Figure 124 for noise margin, and Figure 125. For fuel burn reduction, the the readiness risk continuously increases as uncertainty decreases. The figure provides the S/N and WPV. POS is not provided because the POS goes to 0% by Reduction 2. The performance risk trend communicates that the mean value and WPV are continuously decreasing.

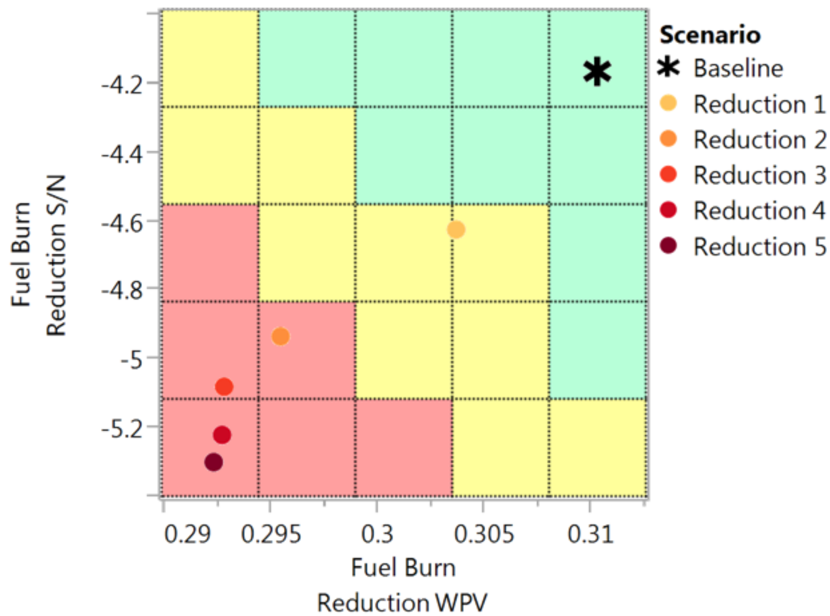

Figure 123: Progression of fuel burn performance risk for Portfolio 20.

For noise margin, the performance risk is steadily decreasing as the uncertainty decreases. The mean value and WPV both increase over time as the uncertainty surrounding the response diminishes. The POS of meeting the set goal for noise margin reaches 100% at Reduction 2. Lastly, for NOx emissions the trend communicates that the mean value decreases as uncertainty is reduced but the WPV increases. This indicates that the distribution shifts downwards but the left tail of the distribution shrinks. Therefore, while the expected value of NOx emissions is continuously decreasing the worst-case scenario improves over time. Lastly, the POS for the NOx emissions goal reaches 0% by Reduction 2.

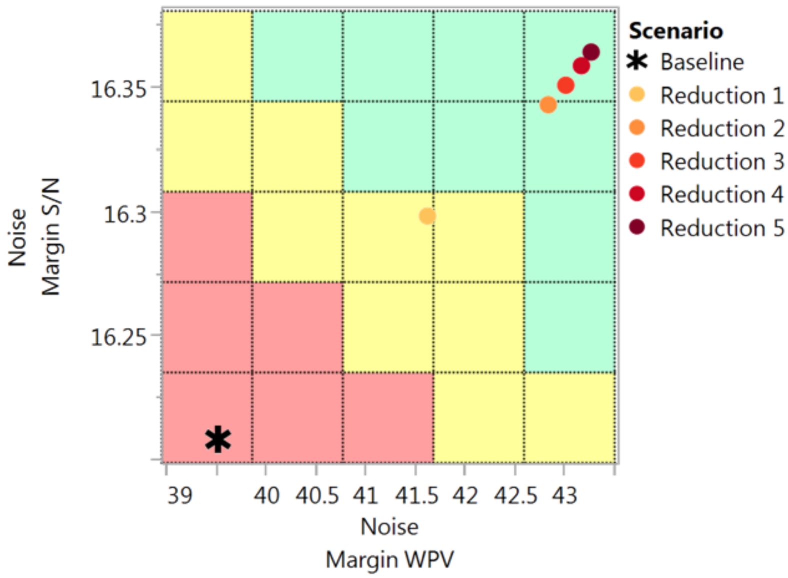

Figure 124: Progression of noise margin performance risk for Portfolio 20.

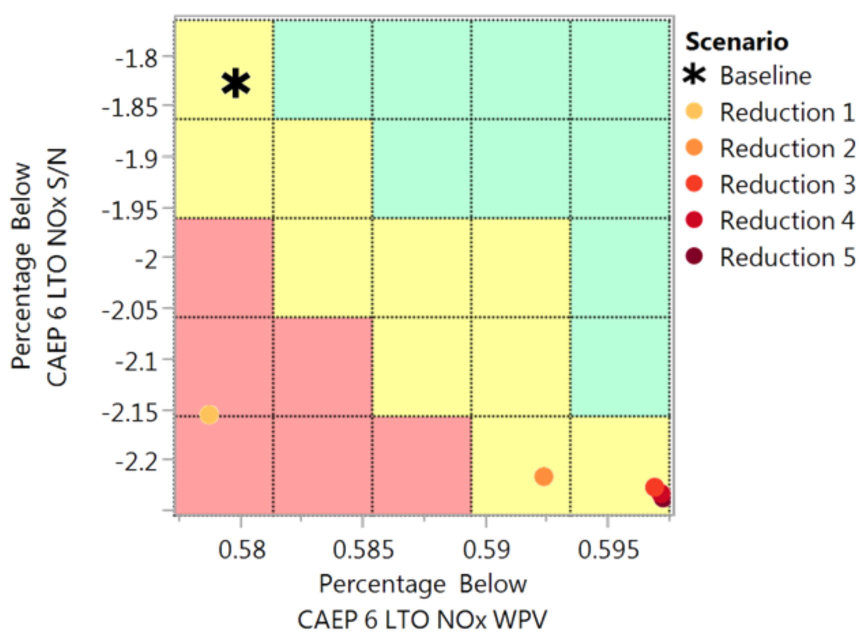

Figure 125: Progression of NOx performance risk for Portfolio 20.

The trends described by the performance risk depictions are confirmed through the progression of the objective metrics' PDFs provided in Figure 126. It is clear that fuel burn reduction and NOx emissions continuously degrade and converge to values less than the set goals. In order to determine what is driving the degrading fuel burn and NOx performance, the technology-level performance risk for the technologies that drive fuel burn and NOx were examined.

Recall, Figure 119 identified T69.1 as the main driver of fuel burn reductions variance and POS before any uncertainty was reduced. Figure 127 provides T69.1's performance risk progression for fuel burn reduction. It is observed that the mean fuel burn reduction decreases as T69.1's technology uncertainty decreases. Table 37 displays the progression of the expected performance delta T69.1 provides for fuel burn reduction. The expected performance of T69.1 degraded from a potential 10.39% reduction in fuel burn to a 6.74% reduction in fuel burn, which is almost a 4% difference.

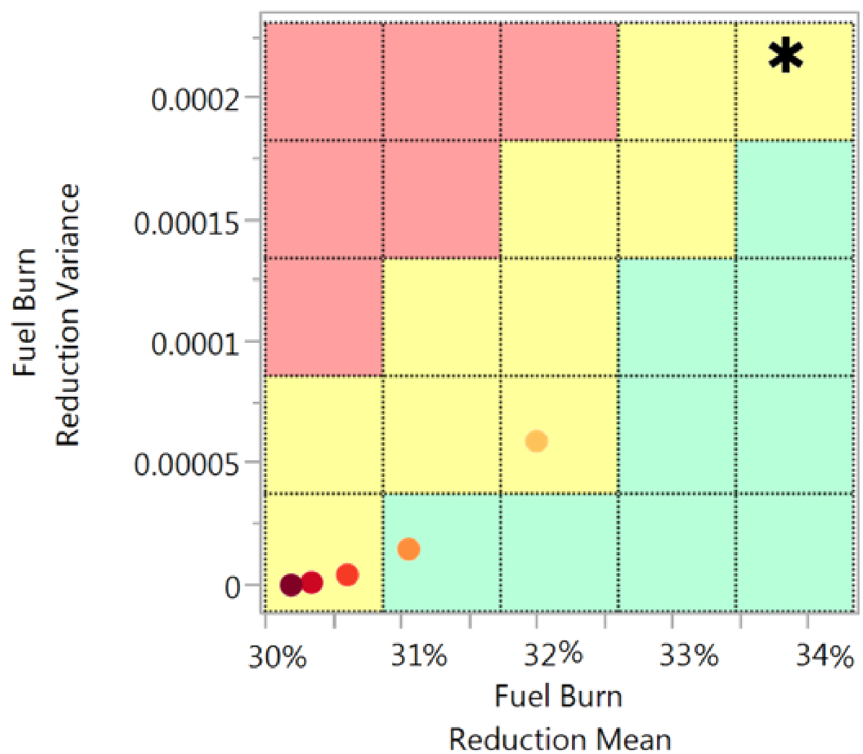

Figure 127: Progression of fuel burn reduction performance risk for T69.1.

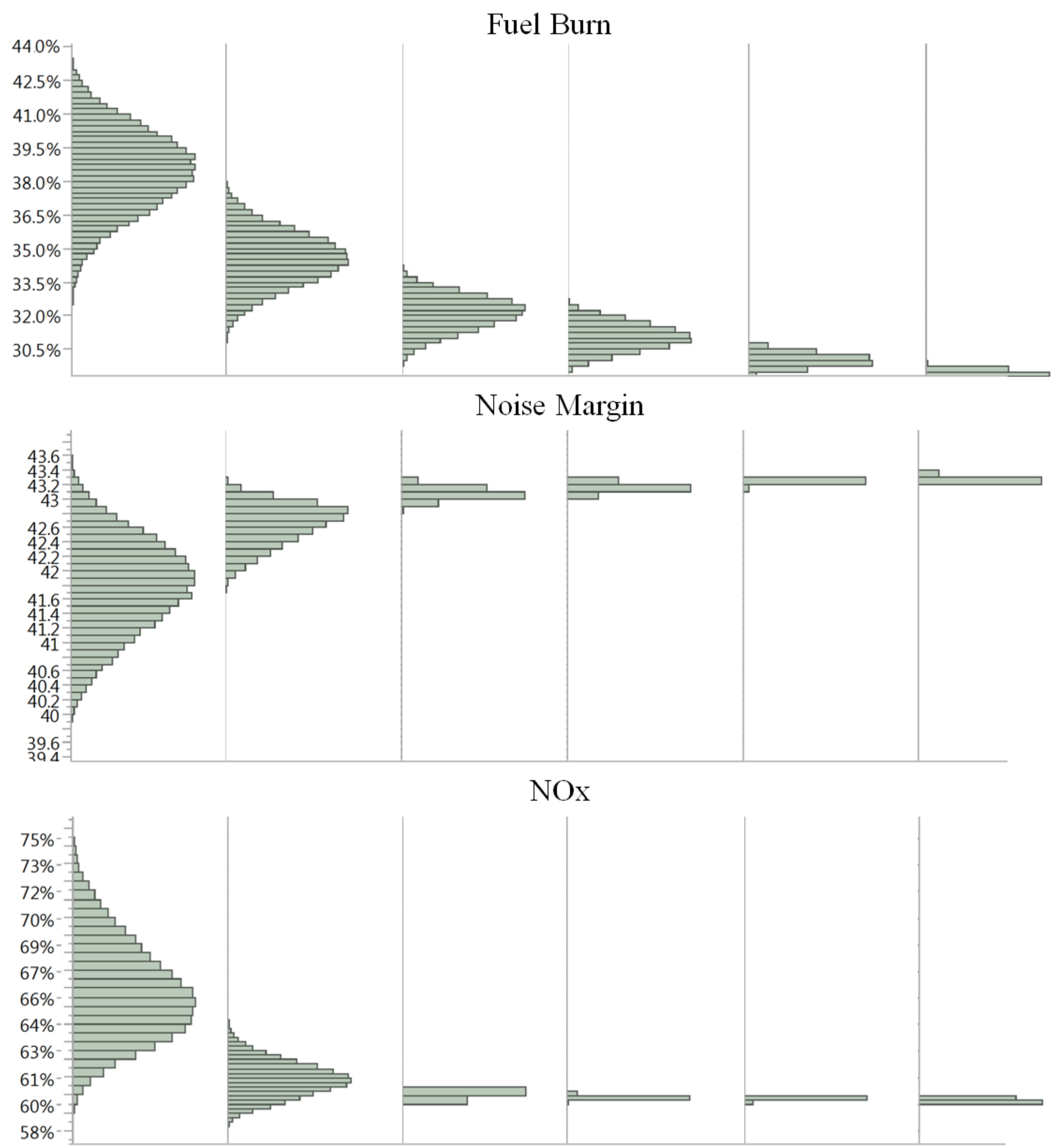

Figure 126: Progression of objective metrics' PDFs over time.

Table 37: Progression of fuel burn reduction performance delta for T69.1.

Scenario	Performance Delta
Baseline	10.39%
Reduction 1	8.55%
Reduction 2	7.61%
Reduction 3	7.17%
Reduction 4	6.90%
Reduction 5	6.74%

The portfolio-level performance risk progression enabled the identification of degrading fuel burn reduction and NOx emissions performance. Furthermore, the investigation of the technology-level performance risk progression for T69.1 enabled the identification of a technology that is driving the fuel burn performance risk of the entire portfolio in a negative direction. Based on this information, decision makers could determine if the 6.74% fuel burn reduction is acceptable and the technology is still worth pursuing. Similar assessments would then be performed for each technology within the portfolio. The results of the performance risk assessments and the readiness risk assessments would be used together to aid decision makers in ultimately determining if a technology, or set of technologies, is ready for transition into system development.

7.5 Investigation of Risk Mitigation

The preceding sections have outlined in detail the QuantUM^3 methodology developed within this research. It was demonstrated through implementation on an HWB case study how performance risk and readiness risk are calculated, depicted, and tracked throughout development to aid risk-informed decision making. However, it was acknowledged in Chapter Four that even when risk-informed decisions are made, risky scenarios can still arise throughout the development program. When this occurs, the risk must be accepted or plans must be put in place to mitigate it.

It was hypothesized in Hypothesis 5.1 that the need for performance risk mitigation, readiness risk mitigation, or both can be identified through the previously defined risk depictions and and the POS values for the objective metrics. The work shown in the previous section demonstrated how the combined information provided by the enumerated performance risk and readiness risk depictions at the portfolio-level and technology-level enable identification of unfavorable risk trends. This information was used in Phase 4 to determine whether a single technology or set of technologies are worthy of transition into system development. However, this information is also available throughout development. The importance of continuously updating the risk depictions was discussed, therefore risky performance or readiness trends can be identified before a technology development program comes to an end. These observations confirm Hypothesis 5.1 and no further experimentation is required.

Hypothesis 5.2 stated that regularly updated risk analyses can also aid the identification of potential avenues for risk mitigation. This hypothesis was tested by conducting further investigation of the HWB case study. Recall, it was identified in the last section that T69.1 showed degrading performance throughout development and was a cause of the degrading fuel burn reduction performance risk for the entire portfolio. Through further investigation into the other technologies within the portfolio it was discovered that T80.2, which was identified in Figure 119 as the second most important technology contributing to fuel burn reduction, is also experiencing degrading performance. Table 38 shows the progression of the expected performance delta for fuel burn reduction. Initially, it was anticipated that T80.2 would provide a 2.73% fuel burn reduction. However, after further development the technology is anticipated to provide only a 0.24% fuel burn reduction from the 2010 baseline vehicle.

Table 38: Progression of fuel burn reduction performance delta for T80.2.

Scenario	Performance Delta
Baseline	2.73%
Reduction 1	2.29%
Reduction 2	1.93%
Reduction 3	1.49%
Reduction 4	0.66%
Reduction 5	0.24%

Combining the information from Table 37 and Table 38, the portfolio experienced a decrease in the expected fuel burn reduction from these two technologies of 6.5%. This is a situation that could be considered a high performance risk, and decision makers would potentially wish to mitigate this risk. If risk mitigation is desired, a plan that attempts to remedy the fuel burn reduction performance would be required. Recall, during Phase 2 of development supplemental technologies were selected to be backup technologies. However, neither of these technologies were selected for their fuel burn impact so they are not relevant to mitigate the identified risk.

In this situation, improvement of fuel burn reduction could only be achieved by selecting a new technology that improves the fuel burn reduction provides a positive anticipated performance benefit. Potential technologies can be identified by utilizing results of previous analysis conducted within the methodology implementation. Recall, the OAT experiments provided a ranking of the technologies based upon how they affect the objective metrics. Table 34 provided the ranking for fuel burn reduction. It is identified that T10.1 provides an anticipated fuel burn benefit of an 8.42% reduction below the 2010 baseline and is therefore selected as the potential risk mitigation technology.

The next step is to analyze how the new portfolio would perform and how its readiness risk would change if T10.1 was added. There are two different identified scenarios that could occur if T10.1 was added to the portfolio. First, Portfolio 20 could be augmented by excluding T69.1 and including T10.1. The second is Portfolio 20 could be augmented by excluding both T69.1 and T80.2 and including T10.1. It is not possible to exclude only T80.2 and include T10.1 because T10.1 and T69.1 and incompatible technologies.

Both of the defined scenarios were analyzed to obtain the performance risk analysis. The initial baseline uncertainty depiction for T10.1 was utilized because it has not undergone any development since Phase 1. However, the final uncertainty depictions for the technologies in Portfolio 20 are used because they have undergone experimentation. Table 39 shows the results for the expected values of the objective metrics. Note that the inclusion of T10.1 and exclusion of T69.1 provides a fuel burn reduction benefit of 1.63% above Portfolio 20 and the exclusion of both technologies provides a benefit of 1.43%. Furthermore, both mitigation scenarios provide minor improvements for noise margin and NOx emissions when compared to Portfolio 20.

Table 39: Comparison of expected performance for objective metrics when T10.1 is considered for risk mitigation.

Scenario	Fuel Burn Reduction	Noise Margin	NOx Emissions
Port 20	29.48%	43.288	59.74%
Port 20-T69.1+T10.1	31.11%	44.682	60.07%
Port 20-both+T10.1	30.90%	44.711	60.05%

Studying just the expected value of the objective metrics does not provide the entire story because the uncertainty added by T10.1 and the readiness risk must also be considered. T10.1 is less developed than the other technologies and therefore it is expected to have more performance uncertainty and a higher readiness risk. Figure 128 shows the performance risk comparison for the three scenarios. The S/N ratio increases for both risk mitigation scenarios. It was shown above that the risk mitigation scenarios have a slightly larger mean, which causes the S/N to increase. However, it also shows that the uncertainty introduced by T10.1 is not driving the S/N. Furthermore, is acknowledged that the WPV decreases for both mitigation scenarios in comparison to Portfolio 20. Therefore, the uncertainty from T10.1 causes the worst case scenario to be approximately 2.5% less than Portfolio 20.

Figure 129 shows the readiness risk comparison for Portfolio 20 and the two risk mitigation scenarios. It is observed that both the average TRL and average number of years until TRL 9 is achieved increases for the mitigation scenarios, which causes the readiness risk to jump from a low risk (green) portion of the risk depiction to the mid and high risk portions. This is expected because T10.1 has not yet been further developed. While the differences are very small for both readiness risk measures, Scenario 2 provides a better readiness risk than Scenario 1.

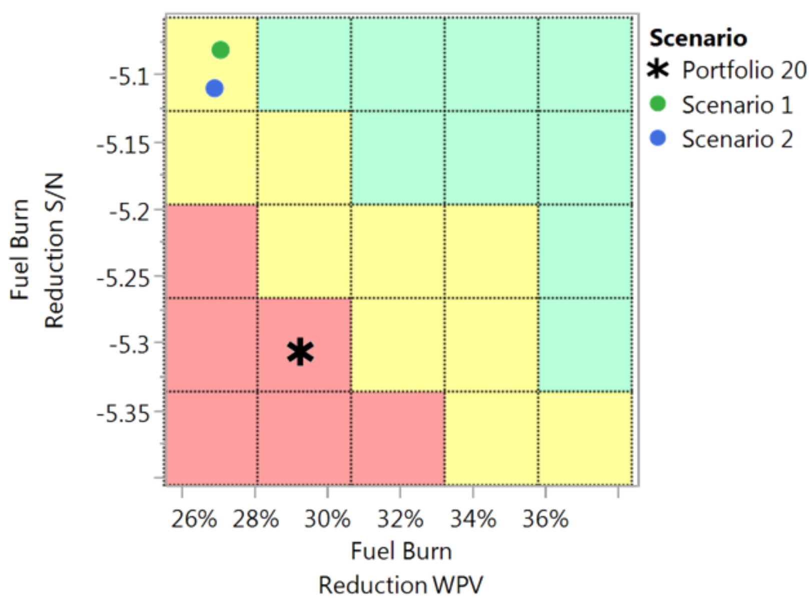

Figure 128: Fuel burn reduction performance risk T10.1 risk mitigation scenarios.

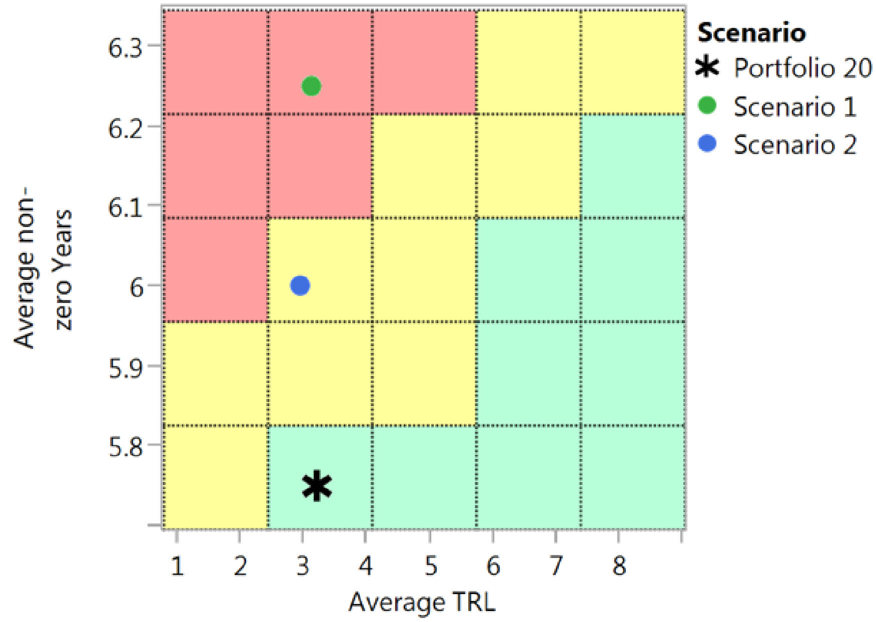

Figure 129: Readiness risk for T10.1 risk mitigation scenarios.

The risk analyses and formulation of the readiness risk depictions and the performance risk depictions provide a clear picture of how effective T10.1 could be as a risk mitigation activity. The information provided by the risk depictions show that Scenario 1 provides the best expected performance and a better performance risk than Scenario 2. Scenario 2 provides a better expected performance than Portfolio 20 and has a better readiness risk than Scenario 1. Next, decision makers would have to take this information and determine if either of the risk mitigation strategies provided would be worthwhile to the technology development program as a whole.

This demonstration demonstrates how the methodology as a whole facilitates the development of risk mitigation plans. Analysis conducted in early steps of the methodology provide relevant information for developing potential plans, and the processes put in place for later steps of the method can be leveraged to assess the value of the risk mitigation plans. Based upon these observations and the case study demonstration, it is concluded that Hypothesis 5.2 is confirmed.

CHAPTER VIII

CONCLUSIONS

8.1 Summary of Research Findings

The QuantUM^3 methodology was formed to fulfill the stated research objective, which was to provide a process that involves quantitative performance assessments and qualitative readiness assessments to aid risk-informed technology development decisions. The methodology includes quantitative, probabilistic performance assessments that provide the expected performance of technologies and the impact the technologies' uncertainty has on the system level performance. It also includes the use of existing readiness metrics and assessment processes to evaluate the overall readiness of a single technology and the anticipated difficulty in increasing the readiness.

A set of research questions and hypotheses were presented that architected the overall QuantUM^3 methodology. The methodology focuses on providing readiness risk and performance risk information to enable risk-informed decisions throughout all four phases. Decision scenarios for each decision were enumerated and risk measures that provide relevant information were enumerated. The experiment sets planned and performed within this research tested the hypotheses by developing processes that enabled the calculation of the potential risk measures and testing the capability of the measures on each of the identified decision scenarios.

Research Questions 1.1-1.3 addressed the objectives of *Strategic Planning*, which is architecture selection and the identification of key impacts. It was proposed through Hypothesis 1.1 that a model-driven environment paired with a probabilistic forecasting analysis would enable vehicle architecture performance comparisons based upon the future potential of the architecture alternatives. Experiment set 1 tested this hypothesis by utilizing the EDS modeling environment to capture the environmental objectives metrics of the ERA program. The results of the experiment confirmed that the outlined forecasting analysis could be used to compare two different vehicle architectures, such as a hybrid wing body and tube and wing vehicle.

Hypotheses 1.2 suggested that a sensitivity analysis could be used with the modeling environment to produce a ranked set of important impacts. Furthermore, it was hypothesized in Hypothesis 1.3 that the results of a probabilistic forecasting analysis could be used to identify relevant impact scenarios, which would provide the amount of improvement required for the identified key impacts. The second part of Experiment set 1 tested these processes and it was concluded that surrogate models and an ANOVA assessment can provide a ranked list of technology impacts for objective metrics of interest. Finally, the probabilistic results can be filtered to identify combinations of component level capabilities tat enable the specific performance goals to be met for a given vehicle architecture. These observations and conclusions overall support Hypotheses 1.2 -1.3.

Research questions 2.1-2.4 addressed the objectives of *Technology Selection*. Research question 2.1 focused on how to properly formulate a set of technology portfolios. It was hypothesized that technologies should be prioritized based upon their performance impact, and that the information from *Strategic Planning* on the key impacts would be sufficient. Research questions 2.2 and 2.3 addressed the proper analysis procedures for quantifying readiness risk and performance risk for each of the portfolios under consideration. It was hypothesized that aggregate measures of readiness and development difficulty would properly capture readiness risk and POS and a measure that captures the tail end of the distribution would properly capture performance risk. Lastly, research question 2.4 addressed how supplemental technologies should be selected. It was hypothesized in Hypothesis 2.4 that information on how each technology drives the POS would be sufficient to make performance-based decisions.

Experiment set 2 tested Hypotheses 2.1-2.4. It was observed that a set of technologies may not be provided to a technology development program, as was assumed for this research. Identification of relevant technologies could be achieved by utilizing the identified key impacts driving the objective metrics and the impact scenarios. It was concluded that when this method is utilized, further prioritization of the technologies may be required if the set of technologies is too large to formulate and analyze all potential technology portfolios. This research focused on prioritizing technologies based upon how their individual performance impact. It was concluded that a two phase performance prioritization would be required when a large set of technologies exists. A process, called the OAT analyses, were created to determine the impact a technology has on the three objective metrics. Therefore, Hypothesis 2.1 was partially supported and the final form was augmented to include the two-tier prioritization process.

The second part of Experiment Set 2 focused on outlining the processes required to calculate the relevant readiness risk and performance risk measures and evaluating the adequacy of those measures with regards to the identified decision scenarios. For readiness risk, it was concluded that a cardinal version of the TRL scale provides aggregate TRL measures. Furthermore, it was concluded that the type of difficulty that should be captured is the inherent difficulty among technologies for achieving a set level of readiness. This type of difficulty was captured by using available data on the number of years until TRL 9 was anticipated. The resulting readiness risk depictions were able to communicate the decision scenarios and Hypothesis 2.2 was therefore supported. For performance risk, an uncertainty quantification process was outlined that utilized Monte Carlo sampling and artificial neural networks to facilitate the calculation of the identified performance risk measures. It was concluded that S/N could represent the expected value and spread of the objective metrics and therefore be used as a measure of likelihood for performance risk when POS inhibits technology portfolio comparisons. For measures of consequence, it was observed that using WPV over TCE creates more of a spread in the data, which enables a better prioritization. Therefore, the Hypothesis 2.3 was partially supported.

The final part of Experiment Set 2 produced a process for analyzing the sensitivity of the performance objectives to each technology in the selected portfolio. The portfolio-specific OAT experiments, P-OAT experiments, were created to calculate the sensitivity of the POS of each objective metric to each of the technologies and the results were depicted through a set of waterfall charts. It was concluded that the creation of this information does enable performance comparisons among technologies in a technology portfolio, so Hypothesis 2.4 is supported.

Research question 3.0 addressed the proper way to measure and communicate technology readiness. It was hypothesized that a morphological readiness assessment based upon the TRL scale could provide a clear, traceable readiness measurement and communication tool. The first part tested Hypothesis 3.0 by outlining the morphological readiness assessment approach and testing its ability to measure and communicate TRL on the PRSEUS material technology. It was concluded that the morphological readiness assessment is traceable, repeatable, and straightforward, which therefore supports Hypothesis 3.0.

Research questions 3.1-3.3 addressed how to prioritize technologies for experimentation and then how to plan required experimentation for a single technology. It was hypothesized that the TRL and development difficulty for the individual technologies can be used to prioritized based upon readiness risk. Furthermore, it was proposed that the amount of uncertainty and affect the uncertainty has on the performance of the entire portfolio can be used for performance-based prioritization. Finally, an experiment design process that combines the information provided by the morphological readiness analysis and quantitative uncertainty analysis was proposed. The second part of the experiment set utilized the morphological readiness assessment to formalize the experiment design process by pairing it with quantitative uncertainty analysis techniques. The experiment design process was demonstrated and it was observed that it has the ability to recommend the type of experiment, what should be tested, and the type of measurements that are required to reduce uncertainty. Therefore, hypotheses 3.1-3.3 are supported.

Research questions 4.1 and 4.2, and their corresponding hypotheses, addressed the objectives of *Technology Transition Readiness Assessment*. It was proposed that monitoring the progress of a technology at the technology-level will provide enough information to decision makers at the end of a development program to determine what should become of the technologies. For Experiment Set 4, performance and readiness progression scenarios were created for a single technology portfolio to simulate the experimentation performed in a technology development program. The performance risk and readiness risk of each scenario was then analyzed and plotted on the previously defined risk depiction charts. Through the identification of ideal and non-ideal risk trends, it was concluded that it is important to observe the risk progressions at both the individual technology-level and the portfolio-level in order to see the complete risk picture. Furthermore, it was concluded that mean and variance are best suited for tracking performance risk at the technology-level. Based on these Hypotheses 4.1 and 4.2 were partially confirmed and the final answers were augmented to include the required risk assessments at both levels.

The final set of research questions addressed the ability of the QuantUM^3 methodology to aid risk management and mitigation. Experiment Set 5, involved a complete demonstration of the QuantUM^3 methodology. After the implementation of the methodology, the risk mitigation capabilities of the defined processes and risk measures were tested. It was observed that the need for risk mitigation could be identified by using the previously defined risk depictions at both the technology-level and portfolio-level. Furthermore, it was concluded that potential risk mitigation plans could be identified by using the results of past development phases and the plans could then be assessed through the same analysis procedures. Therefore, Hypotheses 5.1 and 5.2 are supported.

The final implementation of the QuantUM^3 methodology verifies that the methodology provides a repeatable and transparent process that enables risk-informed decisions throughout technology development. QuantUM^3 fills an identified gap of synthesizing SME-based readiness assessments and quantitative performance assessments to provide a clearer risk depiction. Furthermore, QuantUM^3 provides the ability to track how decisions made throughout development determine the type of performance that can be expected. This benefit is demonstrated through the progression of probabilistic performance assessments shown in Figure 130. The first performance assessment was the forecasted performance for each of the three architectures. Next, after the HWB concept was selected, new performance goals were set and the impact scenarios were identified. Technology portfolios were then formulated and their expected performance is compared to the original HWB performance analysis. Portfolio 20 was then selected and the technologies were further developed, which resulted in a reduction of uncertainty and shift in the expected performance.

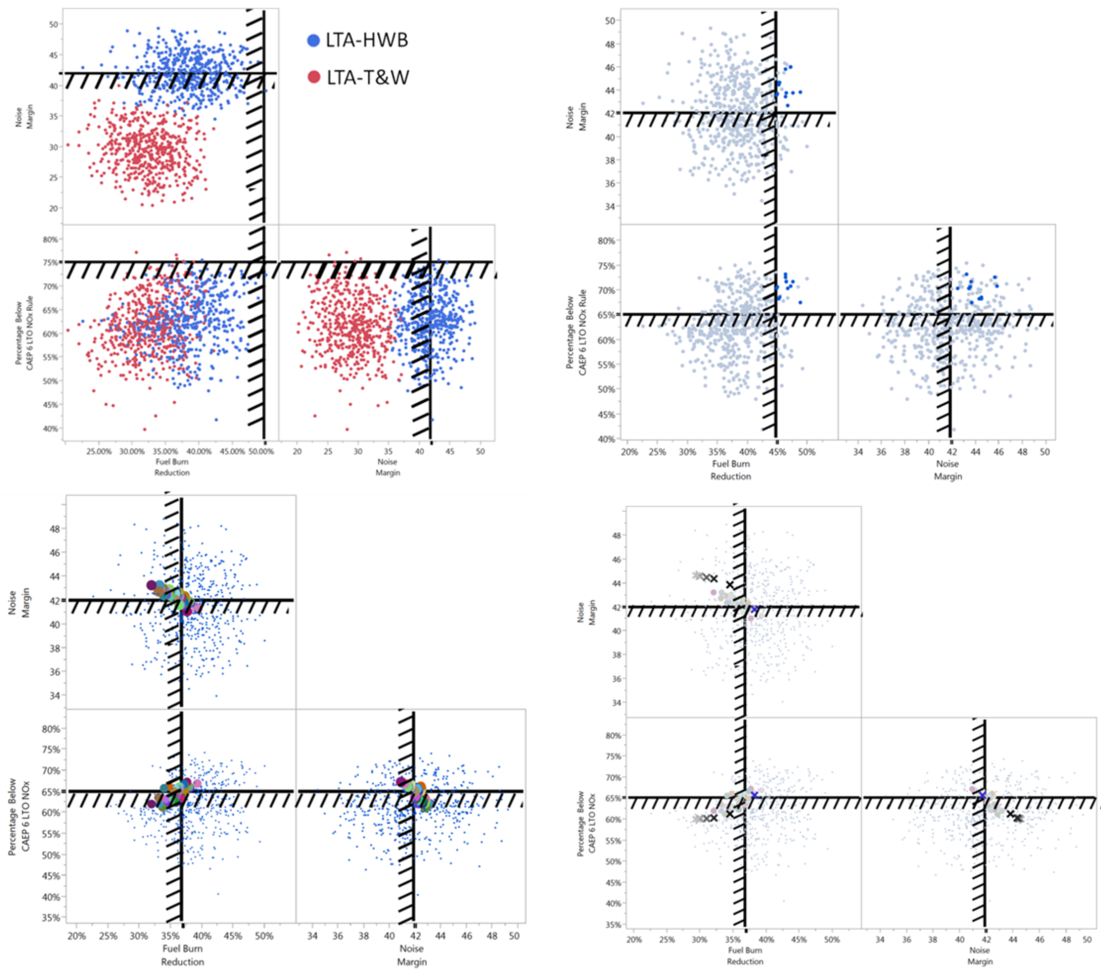

Figure 130: Progression of probabilistic results for HWB vehicle throughout the QuantUM^3 methodology implementation.

Altogether, QuantUM^3 provides an improvement in the current state of the art with respect to integrated, technology development assessment techniques. It provides methods for calculating and tracking readiness risk and performance risk and encompasses all important key decisions that must be made within a technology development program. Implementation of this this methodology will provide a means for prioritizing architecture and technology alternatives and planning required experimentation that will simultaneously increase the readiness and decrease the performance uncertainty.

The full implementation confirmed that the QuantUM^3 methodology utilizes both uncertainty quantification methods and qualitative readiness assessment methods to aid the calculation and communication of both readiness risk and performance risk. It encompasses all identified important steps of technology development, including technology portfolio selection, experimental planning, and transition readiness assessment. Finally, the methodology recommends the use of performance and readiness risk depictions that are relevant to each step. Altogether, the QuantUM^3 methodology also improves the current state of the art by providing an integrated, traceable process that synthesizes all available information to facilitate risk-informed decision making. Based upon all of this information, it is established that the work conducted within this thesis meets the stated formal research objective.

8.2 Summary of Contributions

This work resulted in several contributions to the fields of probabilistic performance analysis and technology readiness analysis. First, the resulting integrated methodology synthesizes quantitative, probabilistic performance results with qualitative, subjective, SME-based readiness assessments to enable risk-informed technology development decision making. Previous to this work, there was a gap in existing methodologies regarding the integration of results from these two different analysis techniques. The new methodology provides an extensive amount of information to decision makers that can be used to facilitate trade-offs and down-selections.

Another contribution is the defined process for technology portfolio formulation. It is a process that formulates potentially viable technology portfolios through a two-tier technology prioritization process that considers the contribution technologies have at the component level as well as their impact at the system level. Existing technology portfolio formulation methods identify high-performing portfolios, but they do not take into consideration the uncertainty of under-developed technologies or limitations on the number of technologies desired per potential portfolio.

A third contribution is the development of a readiness assessment method that used morphological analysis to decompose the TRL definitions and clearly communicate the expected experimentation relevant to each level of the scale. The morphological analysis was a building block for the fourth contribution, which is the experiment design process that was outlined and implemented within this research. It is a process that prioritizes technologies for further development based upon the impact of their existing performance uncertainty and plans experimentation that targets high-impact uncertainty sources to facilitate the simultaneous reduction of uncertainty and increase of overall readiness. This process differs from existing experiment design philosophies because it does not assume the amount of uncertainty that will be reduced from a provided experimental plan can be pre-determined. This is important because it was identified that this assumption may not hold true in a real-world technology development environment. Furthermore, the experiment design method developed in this research synthesizes information from the TRL measurement process and uncertainty quantification analysis.

The final contribution is the identification and implementation of a set of performance risk measures and depictions that enable the progression of performance risk to be clearly communicated and the identification of negative risk trends throughout technology development. This is an important contribution because it aids risk mitigation throughout the course of the development program. Furthermore, early identification of non-ideal risk trends allows for a more successful development program in the future.

8.3 Summary of Future Work

Several areas have been identified for potential extensions of this research. This research focused on utilizing a system-level modeling environment for the performance assessments. However, as technologies are developed detailed technology-level models are built. Therefore, the quantitative methods could be expanded to include lower level modeling environments which would expand the level of uncertainty detail available in the probabilistic assessments.

Next, a more quantitative, all-inclusive difficulty assessment method could be developed to fill the current void in difficulty assessment methods. Difficulty measures exist, but most lack a transparent process that enables their calculation. Furthermore, advanced schedule-tracking methods, such as work breakdown structure-based methods, could be incorporated with this research to provide a way to track schedule risk or provide difficulty information in a more detailed manner.

The methodology could be augmented to address more types of risk. Methods that quantify other types of risk beyond performance risk and readiness risk could be included to provide supplemental information that would be used in a similar manner to enable risk-informed decision making.

Lastly, it was identified that the exploration of the effect of different uncertainty characterization methods on the results of the system level assessments could be investigated. Methods for technology uncertainty characterization were outside the scope of this research and triangular distributions were formed based upon the provided technology impact data. However, other distribution types could be experimented with and the sensitivity of the results could be assessed.

APPENDIX A

DEFINITION OF TECHNOLOGIES

This research utilizes a set of technologies that were previously identified as relevant to the NASA ERA project. Information describing the technologies and their defining performance characteristics was taken from a technology report produced by the Aerospace Systems Design Laboratory at the Georgia Institute of Technology. The technologies within this set were included due to the nature of the expected performance impact and their development time line. The ERA program focuses on technologies that will achieve TRL 6 by the year 2025.

The information provided for each technology includes a 3-point estimate of each performance impact, the current TRL, and the number of years until TRL 9 is achieved. This information was gathered by the ASDL team through literature search and a series of workshops with relevant SMEs. The provided performance impact information was utilized within this research to facilitate probabilistic performance assessments. Each impact for each technology was mapped to a relevant k-factor in the EDS environment. The 3-point estimates were used to form triangular distributions, where the minimum and maximum values bound the distribution and the mid-point value was the peak of the distribution.

The following sections provide the technology identifier, technology name, readiness information, and 3-point impact information for each of the 88 technologies considered within this thesis. The technologies have been divided into groups based upon how they fundamentally impact the aircraft system. Six different technology groups exist and they are: engine fuel burn technologies, engine noise technologies, airframe aerodynamic technologies, airframe noise technologies, engine emissions technologies, structure and subsystem technologies.

A.1 Engine Fuel Burn Technologies

T7: Solid Oxide Fuel Cell Auxiliary Power Unit

Current TRL: 3

Years until TRL 9: 17.5

Variable	min	mid	max
WAPU	0	0.63211	2

T20: Active Compressor Clearance Control

Current TRL: 3

Years until TRL 9: 11

Variable	min	mid	max
HPC_ Deff	0.0025	0.01	0.02
HPX	0	0.5	2
sAccess_ Wt	0.015426	0.01714	0.023996

T21: Active Compressor Flow Control

Current TRL: 3

Years until TRL 9: 15

Variable	min	mid	max
HPC_ AFC_ nStages	1	2	4
HPC_ FlowControl	0.005	0.01	0.02
HPC_ AFC_ LossRatio	0.12	0.25	0.5
sAccess_ Wt	0.010287	0.01143	0.016002

T22.1: Compressor Intercooler

Current TRL: 2

Years until TRL 9: 14

Variable	min	mid	max
IntercoolerHX_ effect	0.7	0.85	0.9
LPCPR	0	0.15022	0.704
IntercoolerBleedFlow	0.04	0.059	0.08
IntercoolerCoreDP	0.02	0.032	0.05
IntercoolerNondimensionalWeight	8	9.653	11

T22.2: Cooled Cooling - Turbine

Current TRL: 4

Years until TRL 9: 9

Variable	min	mid	max
HX_ deltaT	100	300	400
HX_ effect	0.7	0.75	0.9
CooledCoolingNondimensionalWeight	6	7.239	9

T23: Active Turbine Clearance Control

Current TRL: 5

Years until TRL 9: 11.5

Variable	min	mid	max
HPT_ eff	0.002	0.009	0.015
LPT_ Deff	0.0005	0.001	0.002
sAccess_ Wt	0.010287	0.01143	0.016002

T24.B: Active Turbine Flow Control

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
LPT_ AFC_ nStages	1	1	2
LPT_ FlowControl	0	0.004	0.015
LPT_ AFC_ LossRatio	0.12	0.25	0.5

T25: Active Film Cooling

Current TRL: 2

Years until TRL 9: 16.5

Variable	min	mid	max
s_ HPT_ ChargeEff	-0.35	-0.25	-0.1
s_ HPT_ NonChargeEff	-0.1	-0.08	-0.05
sAccess_ Wt	0.005139	0.00571	0.007994

T26.1: Advanced Powder Metallurgy Disk - HPC Last Stage Disc

Current TRL: 2

Years until TRL 9: 16.5

Variable	min	mid	max
LPCPR	0.07	0.15022	0.18

T27.1B: N+2 Advanced TBC Coatings - HPT Blade

Current TRL: 6

Years until TRL 9: 6

Variable	min	mid	max
HPT_ delta_ desBladeTemp	50	150	200

T27.2B: N+2 Advanced TBC Coatings - HPT Vane

Current TRL: 6

Years until TRL 9: 6

Variable	min	mid	max
HPT_ delta_ desVaneTemp1	50	150	200
HPT_ delta_ desVaneTemp2	50	150	200

T27.3B: N+2 Advanced TBC Coatings - LPT Blade

Current TRL: 6

Years until TRL 9: 6

Variable	min	mid	max
LPT_ delta_ desBladeTemp	50	150	200

T27.4B: N+2 Advanced TBC Coatings - LPT Vane

Current TRL: 6

Years until TRL 9: 6

Variable	min	mid	max
LPT_ delta_ desVaneTemp	50	150	200

T27.1C: ITD Advanced TBC Coatings - HPT Blade

Current TRL: 7

Years until TRL 9: 6

Variable	min	mid	max
HPT_ delta_ desBladeTemp	50	100	150

T27.2C: ITD Advanced TBC Coatings - HPT Vane

Current TRL: 7

Years until TRL 9: 6

Variable	min	mid	max
HPT_ delta_ desVaneTemp1	50	100	150
HPT_ delta_ desVaneTemp2	50	100	150

T27.3C: ITD Advanced TBC Coatings - LPT Blade

Current TRL: 7

Years until TRL 9: 6

Variable	min	mid	max
LPT_ delta_ desBladeTemp	50	100	150

T27.4C: ITD Advanced TBC Coatings - LPT Vane

Current TRL: 7

Years until TRL 9: 6

Variable	min	mid	max
LPT_ delta_ desVaneTemp	50	100	150

T28.1: Advanced Turbine Superalloys - HPT Blades

Current TRL: 4

Years until TRL 9: 13

Variable	min	mid	max
HPT_ Blade_ rho	0.302	0.307	0.312
HPT_ delta_ desBladeTemp	70	90	100

T28.2: Advanced Turbine Superalloys - HPT Vanes

Current TRL: 4

Years until TRL 9: 13

Variable	min	mid	max
HPT_ Stator_ rho	0.302	0.307	0.312
HPT_ delta_ desVaneTemp1	70	90	100
HPT_ delta_ desVaneTemp2	70	90	100

T28.3: Advanced Turbine Superalloys - LPT Blade

Current TRL: 4

Years until TRL 9: 13

Variable	min	mid	max
LPT_ Blade_ rho	0.302	0.307	0.312
LPT_ delta_ desBladeTemp	70	90	100

T28.4: Advanced Turbine Superalloys - LPT Vane

Current TRL: 4

Years until TRL 9: 13

Variable	min	mid	max
LPT_ Stator_ rho	0.302	0.307	0.312
LPT_ delta_ desVaneTemp	70	90	100

T29.1 + T31: CMC HPT Vane + Hi Temp Erosion Coating

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
HPT_ Stator_ rho	0.18	0.2028	0.23
HPT_ delta_ desVaneTemp1	600	650	675
HPT_ delta_ desVaneTemp2	600	650	675

T29.2: CMC Exhaust Core Nozzle

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
Core_ NOzz_ s_ Wt	-0.35	-0.325	-0.16

T29.3 + T31: CMC LPT Vane + Hi Temp Erosion Coating

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
LPT_ Stator_ rho	0.18	0.2028	0.23
LPT_ delta_ desVaneTemp	600	650	675

T32.B: Highly Loaded Compressor

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
HPC_ Dutip	-380	-337.81	-300
HPC_ FSPRmax	1.7	1.845	1.9
HPCPR	16	20.52212624	22
HPC_ Deff	-0.016	0	0

T33.1: Highly Loaded HP Turbine

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
HPT_ Load	0.25	0.28	0.3

T33.2: Highly Loaded LP Turbine

Current TRL: 4

Years until TRL 9: 13.5

Variable	min	mid	max
LPT_ Deff	0	0.04	0.04
LPT_ Load	0.25	0.28	0.3

T36.5 + T38: Polymer Matrix Composites (PMC) - LPC Stator

Current TRL: 9

Years until TRL 9: 0

Variable	min	mid	max
LPC_ Stator_ rho	0.052	0.052	0.052

T36.6 + T38: Polymer Matrix Composites (PMC) - LPC Blade

Current TRL: 9

Years until TRL 9: 0

Variable	min	mid	max
LPC_ Stator_ rho	0.052	0.052	0.052

T67: Advanced Engine Components

Current TRL: 3

Years until TRL 9: 9

Variable	min	mid	max
Fan_ Deff	0	0.0025	0.005
HPC_ Deff	0	0.0025	0.005
HPT_ Deff	0	0.0025	0.005
LPC_ Deff	0	0.0025	0.005
LPT_ Deff	0	0.0025	0.005

T77: Variable Area Nozzle

Current TRL: 6

Years until TRL 9: 5

Variable	min	mid	max
Byp_ Nozz_ s_ Wt	0	0.1	0.5

T93.2: Ti-Al - LPT Forward Blades

Current TRL: 9

Years until TRL 9: 0

Variable	min	mid	max
LPT_ Blade_ rho	0.1565	0.1565	0.1565

A.2 Engine Noise Technologies

T40: Fan Vertical Acoustic Splitter

Current TRL: 3

Years until TRL 9: 11

Variable	min	mid	max
Duct15_ dP	0.005	0.008	0.01
DISAP	-3	-1	0
DISTO	-4	-2	0

T41: Blade Tone Control via Trailing Edge Blowing

Current TRL: 4

Years until TRL 9: 20

Variable	min	mid	max
ABTC	0.007	0.009	0.01
DISAP	-5	-3	0
DISTO	-5	-3	0
INLAP	-5	-1	0
INLTO	-5	-1	0

T42: Noise Canceling Stator

Current TRL: 2

Years until TRL 9: 20

Variable	min	mid	max
DISTO	-5	-3	0
INLAP	-5	-1	0
INLTO	-5	-3	0

T47: Fluidic Injection

Current TRL: 3

Years until TRL 9: 20

Variable	min	mid	max
Cust_ Bleed_ Map	0.005	0.01	0.02
Core_ Nozz_ s_ Wt	0.1	0.125	0.15
JETTO	-2.5	-0.5	0

T52: Short Nacelle Lip Liner

Current TRL: 6

Years until TRL 9: 6

Variable	min	mid	max
INLAP	-5	-3	0
INLTO	-3	-1	0

T53: Over the Rotor Acoustic Treatment

Current TRL: 4

Years until TRL 9: 8

Variable	min	mid	max
Fan_ Deff	-0.01	-0.005	0
INLAP	-5	-2	0
INLTO	-5	-2	0

T54: Compound Rotor Sweep

Current TRL: 7

Years until TRL 9: 2.5

Variable	min	mid	max
INLAP	-5	-3	0
INLAP	-5	-3	0

T56: Soft Vane

Current TRL: 3

Years until TRL 9: 15

Variable	min	mid	max
DISAP	-4	-2	0
DISTO	-3	-1	0

T57: Stator Sweep and Lean

Current TRL: 5

Years until TRL 9: 12

Variable	min	mid	max
Fan _ Deff	-0.01	-0.005	0
DISAP	-3.5	-1.5	0
DISTO	-3.5	-1.5	0
INLAP	-3.5	-1.5	0
INLTO	-3.5	-1.5	0

T59: Variable Geometry Chevrons

Current TRL: 6

Years until TRL 9: 5

Variable	min	mid	max
PER1	0.25	0.3	0.35
PER2	0.25	0.3	0.35
S_ BypNozzCv_ lowAlt	-0.01	-0.007	-0.0025
S_ CoreNozzCv_ lowAlt	-0.01	-0.007	-0.0025

A.3 Airframe Aerodynamic Technologies

T10.1: HLFC Suction - Wing

Current TRL: 5

Years until TRL 9:12

Variable	min	mid	max
HPX_ map_ highAlt	150	217.1388	250
WAC	0.5	0.8	1.2
TransREWingUpper	16	20	24

T10.2: HLFC Suction - Tails

Current TRL: 5

Years until TRL 9: 12

Variable	min	mid	max
HPX_ map_ highAlt	150	217.1388	250
WAC	0.5	0.8	1.2
TransREHT	16	20	24
TransREVT	16	20	24

T11.1: Natural Laminar Flow - Wing

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
TransREWingUpper	9	11.5	14

T11.2: Natural Laminar Flow - Tails

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
TransREHT	9	11.5	14
TransREVT	9	11.5	14

T11.3: Natural Laminar Flow - Nacelle

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
TRLN	8.5	40	45
TRUN	8.5	40	45

T12.1: Riblets - Fuselage

Current TRL: 6

Years until TRL 9: 10.5

Variable	min	mid	max
SWETF	-0.06	-0.03	0

T12.2: Riblets - Wing

Current TRL: 6

Years until TRL 9: 10.5

Variable	min	mid	max
s_ CDft_ wing	-0.06	-0.04	-0.01

T66: AFC Tail

Current TRL: 3

Years until TRL 9: 17.5

Variable	min	mid	max
VTVC	-0.3	-0.1	-0.05
SVT	-0.3	-0.1	0

T68: Advanced Aero Wing

Current TRL: 4

Years until TRL 9: 10

Variable	min	mid	max
AR	10.5	11	13
GustLoad	0	0.05	0.1

T69.1: DRE for HLFC - Wing

Current TRL: 4

Years until TRL 9: 12

Variable	min	mid	max
TransREWingUpper	16	20	24

T69.2: DRE for HLFC - Tail

Current TRL: 4

Years until TRL 9: 12

Variable	min	mid	max
TransREHT	16	20	24
TransREVT	16	20	24

T72: Low Interference Nacelle

Current TRL: 3

Years until TRL 9: 14

Variable	min	mid	max
FCDO	-0.006	-0.004	0
sInl_ Nacelle_ thick	-0.66	-0.5	0

T74: Thrust Reversers - Nacelles

Current TRL: 4

Years until TRL 9: 20

Variable	min	mid	max
Byp_ Nozz_ s_ Wt	-0.15	-0.1	-0.05

T94: Adaptive Compliant Trailing Edge

Current TRL: 3

Years until TRL 9: 13

Variable	min	mid	max
GustLoad	-0.4	-0.23	-0.05
VCTE	0.1	0.3	0.5

A.4 Airframe Noise Technologies

T14: Continuous Moldline Link for Flaps

Current TRL: 4

Years until TRL 9: 14.5

Variable	min	mid	max
TEFAP	-7	-3.5	-2
TEFCB	-7	-3.5	-2
TERFSL	-7	-3.5	-2

T15: Flap Fences / Flaplets

Current TRL: 3

Years until TRL 9: 13

Variable	min	mid	max
TEFAP	-5.5	-3.5	-0.5
TEFCB	-5.5	-3.5	-0.5
TEFSL	-5.5	-3.5	-0.5

T16.1: Landing Gear Integration - Main

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
FRLGM	0.01	0.02	0.03
MGRAP	-3	-1.5	0

T16.2: Landing Gear Integration - Nose

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
FRLGN	0.01	0.02	0.03
NGRAP	-3	-1.5	0

T17: Flap Edge Treatment

Current TRL: 4

Years until TRL 9: 14

Variable	min	mid	max
TEFAP	-6	-4	-1
TEFCB	-6	-4	-1
TEFSL	-6	-4	-1

T18: Slat Inner Surface Acoustic Liner

Current TRL: 3

Years until TRL 9: 16

Variable	min	mid	max
LESAP	-6	-4.1	-2

T19: Slat-Cove Filler

Current TRL: 4

Years until TRL 9: 14

Variable	min	mid	max
FRSC	0	0.01	0.02
LESAP	-6.5	-4.5	-2.5

T76: Active Pylons Shaping/Blowing

Current TRL: 3

Years until TRL 9: 11

Variable	min	mid	max
Cust_ Bleed_ Map	0.005	0.01	0.02
JETTO	-1.5	-0.5	0

A.5 Engine Emissions Technologies

T62 + T61: LDI + Active Combustion Control

Current TRL: 4

Years until TRL 9: 9

Variable	min	mid	max
Burnereff	-0.005	-0.0025	0
d_ Burn_ dP	0	0.000128	0.01
HPX	0.5	1	2
T4margin	0	39.6	49.6
sAccess_ Wt	0.010287	0.01143	0.016002

T63: Lightweight CMC Liners

Current TRL: 4

Years until TRL 9: 8

Variable	min	mid	max
Burner_ Liner_ rho	0.069	0.076	0.083

T64 + T61: LPP Combustor w/ TAPS + Active Combustion Control

Current TRL: 5

Years until TRL 9: 8

Variable	min	mid	max
d_ Burn_ dP	0	0.000128	0.01
HPX	3	4	5
T4margin	0	39.6	49.6
sAccess_ Wt	0.010287	0.01143	0.016002

A.6 Structure and Subsystem Technologies

T3.1 : Damage Arresting stitched composites- Fuselage

Current TRL: 6

Years until TRL 9: 10.5

Variable	min	mid	max
FRFU	-0.15	-0.1	-0.05

T3.2 : Damage Arresting stitched composites- Wing

Current TRL: 6

Years until TRL 9: 10.5

Variable	min	mid	max
FRWI	-0.15	-0.1	-0.05

T6: Electro Mechanical Flight Control Actuators

Current TRL: 7

Years until TRL 9: 3

Variable	min	mid	max
HPX	50	125	200
WHYD	-0.2	-0.075	0

T78.1: Primary Structure Joining Methodologies - Wing

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
FRWI	-0.02	-0.01	0

T78.2: Primary Structure Joining Methodologies - Fuselage

Current TRL: 5

Years until TRL 9: 13

Variable	min	mid	max
FRFU	-0.02	-0.01	0

T79.1: Damage Tolerant Laminates - Wing

Current TRL: 2

Years until TRL 9: 14

Variable	min	mid	max
FRWI	-0.02	-0.005	0

T79.2: Damage Tolerant Laminates - Fuselage

Current TRL: 2

Years until TRL 9: 14

Variable	min	mid	max
FRFU	-0.02	-0.005	0

T79.3: Damage Tolerant Laminates - Tail

Current TRL: 2

Years until TRL 9: 14

Variable	min	mid	max
FRHT	-0.02	-0.005	0
FRVT	-0.02	-0.005	0

T80.1: Advanced Sandwich Composites - Wing

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRWI1	-0.2	-0.1	0
FRWI2	-0.15	-0.075	0

T80.2: Advanced Sandwich Composites - Fuselage

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRWI1	-0.2	-0.1	0

T80.3: Advanced Sandwich Composites - Tail

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRHT	-0.2	-0.1	0
FRVT	-0.2	-0.1	0

T81.1: Post-buckled Structure - Wing

Current TRL: 2

Years until TRL 9: 16

Variable	min	mid	max
FRWI	-0.06	-0.03	0

T81.2: Post-buckled Structure - Fuselage

Current TRL: 2

Years until TRL 9: 16

Variable	min	mid	max
FRFU	-0.06	-0.03	0

T82.1: Out-of-Autoclave Composite Fabrication - Wing

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRWI	-0.02	-0.005	0

T82.2: Out-of-Autoclave Composite Fabrication - Fuselage

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRFU	-0.02	-0.005	0

T82.3: Out-of-Autoclave Composite Fabrication - Tail

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRHT	-0.02	-0.005	0
FRVT	-0.02	-0.005	0

T83.1: Unitized Metallic Structures - Wing

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRWI1	-0.1	-0.05	0
FRWI2	-0.04	-0.02	0

T83.2: Unitized Metallic Structures - Fuselage

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRFU	-0.1	-0.05	0

T83.3: Unitized Metallic Structures - Tail

Current TRL: 6

Years until TRL 9: 9

Variable	min	mid	max
FRHT	-0.1	-0.05	0
FRVT	-0.1	-0.05	0

T84.1: Tow Steered Composite Structure - Wing

Current TRL: 4

Years until TRL 9: 19

Variable	min	mid	max
FRWI1	-0.2	-0.1	0
FRWI2	-0.15	-0.075	0

T84.2: Tow Steered Composite Structure - Fuselage

Current TRL: 4

Years until TRL 9: 19

Variable	min	mid	max
FRFU	-0.2	-0.1	0

APPENDIX B

RELEVANT ENVIRONMENTAL DESIGN SPACE VARIABLES

Throughout this research the terms k-factor, or impact variables, is utilized. The k-factors provide a way to represent the impact a technology will have on a future aircraft system. Each technologies is mapped to one or more k-factors, and new values for those k-factors are created to represent the baseline model with the addition of the technology.

The EDS modeling environment utilized for this research has a large number of variables that were identified as potential k-factors. Throughout this dissertation the k-factors have been referred to by their abbreviations. The following sub-sections provide an enumeration of all the abbreviations with their corresponding definitions to provide a better description of the nature of the factors. The variables have been divided into three groups based upon which tool within the EDS environment they come from. Only variables from four of the tools are utilized: the FLOPS tool, the WATE tool, the NPSS tool, and the ANOPP tool.

B.1 FLOPS Variables

TRLH

percent LF horizontal tail lower surface

TRLN

percent LF nacelle lower surface

TRLV

percent LF vertical tail lower surface

TRUH

percent LF horizontal tail upper surface

TRUN

percent LF nacelle upper surface

TRUV

percent LF vertical tail upper surface

TRUW

percent LF wing upper surface

WAC

air conditioning group weight scalar

WAPU

auxiliary power unit weight scalar

FCDO

lift independent drag factor

FCDSUB

factor to increase or decrease all subsonic drag coefficients

FRFU

Fueslage weight factor

FRHT

horizontal tail weight

FRLGM

landing gear weight, main

FRLGN

landing gear weight, nose

FRSC

surface controls weight scalar

FRVT

vertical tail weight

FRWI

total wing weight

FRWI1

first term in wing weigh equation- loosely corresponds to bending material weight

FRWI2

second term in wing weight equation- loosely corresponds to control surfaces, spars and ribs

FRWI3

third term in wing weight equation- loosely corresponds to control surfaces, spars and ribs

VTVC

vertical tail volume coefficient

WHYD

hydraulics group weight scalar

XLLAM

switch to indicate turbulent flow (0) or laminar flow (1)

k_ engpodWt

Factor for bare engine weight to engine pod weight

GW

Ramp weight, lb-Initial guess

AITEK

airfoil technology parameter

AR

wing aspect ratio

CLLDM

maximum CL in landing configuration

DLDWT

delta on FLOPS calculated MLW

FCDI

lift dependent drag factor

NPT

Number of tourist (coach) passengers

PGLOV

Glove to wing area ratio

SW

wing area

TCA

wing thickness to chord ratio (weighted average)

TCHT

thickness to chord ratio for the horizontal tail

TCVT

thickness to chord ratio for the vertical tail

TR

Wing taper ratio

TRLW

percent LF wing lower surface

TWR

thrust to weight ratio- only used for DES run

WCON

cargo and baggage container weight scalar

WSR

wing loading- only used for DES run

XL

fuselage total length, ft

CLTOM

maximum CL in takeoff configuration

FRNA

BLAH

Span_ Efficiency

span efficiency factor for wing

NEF

number of fuselage mounted engines

NEW

number of wing mounted engines

SWEEP

wing quarter chord sweep angle, deg

SWETW

wing wetted area scalar

B.2 WATE Variables

Burner_ Liner_ rho

burner liner material density

Duct15_ rho

Duct 15 material density

Duct4_ LH

Duct 4 length to height ratio

Fan_ Blade_ rho

fan blade material density

Fan_ Case_ rho

Fan case material density

Fan_ numBlades

number of fan blades

Fan_ Stator_ rho

Fan stator material density

HPT_ Blade_ rho

HPT blade material density

HPT_ Stator_ rho

HPT stator material density

LPC_ Blade_ rho

LPC blade material density

LPC_ Stator_ rho

LPC stator material density

LPT_ Blade_ rho

LPT blade material density

LPT_ Stator_ rho

LPT stator material density

Fan_ bladeSolidity

fan blade solidity

HPT_ Load

HPT GE loading

LPT_ Load

LPT GE loading

Byp_ Nozz_ s_ Wt

bypass nozzle weight scalar

Core_ Nozz_ s_ Wt

Core nozzle weight scalar

Bld3_ LH

Bleed 3 length to height ratio

BurnerTime

Burner residence time

BurnerV

Burner velocity

Core_ Nozz_ LDratio

Core nozzle length to diameter ratio

Core_ Nozz_ Plug_ Lratio

Core nozzle plug length to diameter ratio

Core_ Nozz_ rho

core nozzle density

Duct11_ LH

Duct 11 length to heigh ratio

Duct13_ LH

Duct 13 length to height ratio

Duct6_ LH

Duct 6 length to height ratio

Fan_ AR_ Fact

Aspect ratio factor applied to fan blades and stators

Fan_ Duct

Length of duct from rear fan blade to splitter (**Fan_ IGV_ rho**

Fan IGV material density

Fan_ OutIn_ RR

Fan outlet radius to inlet radius ratio

HPC_ AR_ Fact

Aspect ratio factor applied to HPC blades and stators

HPC_ Blade_ rho

HPC blade material density

HPC_ Blade2_ rho

HPC rear blade material density

HPC_ Disk_ rho

HPC disk material density

HPC_ HtoT

HPC hub to tip ratio

HPC_ SolidityFact

solidity factor applied to HPC blades and stators

HPC_ Stator_ rho

HPC stator material density

HPC_ Stator2_ rho

HPC rear stator material density

HPT_ AR_ Fact

Aspect ratio factor applied to HPT blades and stators

HPT_ Disk_ rho

HPT disk material density

HPT_ OutIn_ RR

HPT outlet radius to inlet radius ratio

HPT_ SolidityFact

Solidity factor applied to HPT blades and stators

Inl_ Nacelle_ rho

inlet nacelle material density

Inlet_ s_ Wt

Inlet weight scalar

LPC_ Disk_ rho

LPC Disk material density

LPC_ OutIn_ RR

LPC outlet radius to inlet radius ratio

LPC_ SolidityFact

solidity factor applied to LPC blades and stators

LPT_ AR_ Fact

Aspect ratio factor applied to LPT blades and stators

LPT_ Disk_ rho

LPT disk material density

LPT_ OuterRadius

Ratio of LPT inlet tip radius to reference tip radius

LPT_ OutIn_ RR

LPT outlet radius to inlet radius ratio

LPT_ SolidityFact

solidity factor applied to LPT blades and stators

s_ Fan_ Blade_ rho

fan blade material density scalar multiplier

s_ Fan_ Stator_ rho

fan stator material density scalar multiplier

s_ HPC_ Blade_ rho

HPC blade material density scalar multiplier

s_ HPC_ Blade2_ rho

HPC rear blade material density scalar multiplier

s_ HPC_ Stator_ rho

HPC stator material density scalar multplier

s_ HPC_ Stator2_ rho

HPC rear stator material density scalar multiplier

s_ HPT_ Blade_ rho

HPT blade material density scalar multiplier

s_ HPT_ Stator_ rho

HPT stator material density scalar multiplier

s_ LPC_ Blade_ rho

LPC blade material density scalar multiplier

s_ LPC_ Stator_ rho

LPC stator material density scalar multiplier

s_ LPT_ Blade_ rho

LPT blade material density scalar multiplier

s_ LPT_ Stator_ rho

LPT stator material density scalar multiplier

LPT_ deltaPhi

LPT flow coefficient delta- used for tuning model with new logic

GustLoad

gust load sizing load as a percent of normal

sAccess_ Wt

Engine accessories weight fraction of bare engine weight

sInl_ Nacelle_ thick

Nacelle radius delta scalar

Fan_ stator

If 1, stator is located at LPC exit

LPT_ Blade2_ rho

LPT blade material density

LPT_ Stator2_ rho

LPT stator material density

B.3 NPSS Variables

Ext_ Ratio

Extraction ratio at Aero Design Point

FPR

FPR at aero design point

GearRatio

Low shaft gear ratio

HPC_ AFC_ nStages

Number of HPC stages to apply AFC efficiency gain to

HPC_ Dutip

HPC tip speed delta at aero design point

HPC_ FSPRmax

Maximum HPC 1st stage PR

HPCPR

HPCPR at aero design point

IntercoolerHX_ effect

Intercooler heat exchanger effectiveness

LPCPR

LPCPR at aero design point

numBypNozDiamLong

number of nozzle diameters engines located longitudinally upstream the trailing edge

numBypNozDiamVert

number of nozzle diameters engines located vertically above vehicle

ABTC

Bleed flow required for ABTC

ATD_ BleedFlow

Bleed flow injected in the duct before the LPT

Burnereff

Burner efficiency

CirculationControlFlow

flow required for circulation control

HX_ deltaT

Cooled cooling flow temperature drop across heat exchanger

Cust_ Bleed_ Map

Engine customer bleed (function of ambient)

d_ Burn_ dP

Burner pressure drop intercept

Duct15_ dP

Duct 15 pressure drop (bypass duct)

Fan_ Deff

Fan efficiency delta at Aero Design Point (from historical curve)

GearBoxLosses

Percent losses from gearbox- Applied to LP shaft

HPC_ Deff

HPC efficiency delta at aero design point

HPC_ FlowControl

Bleed flow required per stage

HPT_ delta_ desBladeTemp

HPT blade temperature increase

HPT_ delta_ desVaneTemp1

HPT vane 1 temperature increase

HPT_ delta_ desVaneTemp2

HPT vane 2 temperature increase

HPT_ eff

HPT adiabatic efficiency at Aero Design Point

HPX

Engine horse power extraction (constant)

HPX_ map_ highAlt

Engine horse power extraction needed above 18000k (function of ambient)

IntercoolerBleedFlow

Intercooler bleed flow from bypass

IntercoolerCoreDP

intercooler core stream dP

LPC_ Deff

LPC efficiency delta at Aero Design Point

LPCStgLoad

LPC Stage loading at aero design point

LPT_ AFC_ nStages

Number of rear LPT stages to apply AFC to

LPT_ Deff

LPT efficiency adder

LPT_ delta_ desBladeTemp

LPT blade temperature increase

LPT_ delta_ desVaneTemp

LPT vane temperature increase

LPT_ FlowControl

Bleed flow required for LPT flow control

PCT_ NOx

Percent Nox reduction

T4margin

Difference in T4 between MTO and MCT

T4max

Maximum T4 (set at Take off)

HPC_ AFC_ LossRatio

Ratio of baseline loss coefficient over loss coefficient with endwall and boundary layer active flow control

HX_ effect

Cooled Cooling heat exchanger effectiveness

LPT_ AFC_ LossRatio

Ratio of baseline loss coefficient over loss coefficient with active flow control

MaxNozzleArea

Maximum amount variable area nozzle can scale

MinNozzleArea

Minimum amount variable area nozzle can scale

S_ BypNozzCv_ lowAlt

Core nozzle velocity coefficient scalar at low altitude

S_ CoreNozzCv_ highAlt

Core nozzle velocity coefficient scalar at high altitude

S_ CoreNozzCv_ lowAlt

Core nozzle velocity coefficient scalar at low altitude

s_ HPT_ ChargeEff

HPT chargeable (exit) cooling effectiveness factor scalar

s_ HPT_ NonChargeEff

HPT non-chargeable (inlet) cooling effectiveness factor scalar

ANOPP_ Detailed_ Switch

Switch to include all ANOPP runs, 0=only overall vehicle Run Only and No NPD runs, 1=Individual component contribution runs and NPD runs

BoundaryLayerIngestion

Boundary layer ingestion switch- 0 is no BLI

CooledCooling

Cooled cooling switch -0

GearedTurboFan

Geared turbofan switch- 0 is direct drive

HPC_ AFC_ Switch

Switch that turns on the efficiency gain on the first two HPC stages

InterCooling

Intercooling switch- 0 is no intercooler

LPT_ AFC_ Switch

Switch that turns on the efficiency gain on the last LPT stages

VariableAreaNozzle

Variable Area nozzle switch- 0 is fixed

ADP_ Alt

Aerodynamic design point altitude (feet)

ADP_ MN

Aerodynamic design point mach number

Burner_ A_ Out

Burner exit area (or HPT inlet area)/HPC inlet area

BypBld_ A_ Out

Bypass bleed outlet/inlet area ratio

Cust_ Bleed

Engine customer bleed (customer)

Duct11_ dP

Duct 11 pressure drop (duct between HPT and LPT)

Duct13_ A_ Out

Core nozzle inlet area/ LPT exit area

Duct13_ dP

Duct 13 pressure drop (LPT and Core Nozzle)

Duct15_ A_ Out

Bypass nozzle inlet area/Bypass duct inlet area

Duct4_ dP

Pressure drop for Duct 4 (duct between splitter and LPC)

Duct6_ dP

Duct 6 pressure drop (duct between LPC and HPC)

Fan_ Dutip

Fan delta tip speed at aero design point (from historical curve)

Fan_ HtoT

Fan hub to tip ratio

Fan_ SM

Fan stall margin at Aero Design point

Fan_ SpecW

Fan specific flow at Aero Design Point

Flat_ dTs

Flat rates delta temperature (STD day in F)

HPC_ A_ Out

HPC exit area/ HPC inlet area

HPC_ fracBldP

Fraction of pressure at HPC interstage bleed

HPC_ fracBldWork

Fraction of work at HPC interstage bleed

HPC_ NcDes

HPC corrected speed at aero design point

HPC_ SM

HPC stall margin at aero design point

HPC_ SpecW

HPC specific flow at aero design point

HPT_ ChargeEff

HPT chargeable (exit) cooling effectiveness factor

HPT_ FlowCoeff

HPT axial flow velocity/ real flow velocity

HPT_ Mn_ out

HPT exit Mach number (sets exit area)

HPT_ NonChargeEff

LPT non-chargeable (inlet) cooling effectiveness factor

HPT_ nStages

HPT number of stages

HPX_ map_ lowAlt

Engine horse power extraction needed below 18000k

LPC_ A_ Out

LPC exit area/LPC inlet area

LPC_ HtoT

LPC tub to tip ratio

LPC_ SM

LPC stall margin at aero design point

LPC_ SpecW

LPC specific flow at Aero design point

LPT_ ChargeEff

LPT chargeable (exit) cooling effectiveness factor

LPT_ NonChargeEff

LPT non-chargeable (inlet) cooling effectiveness factor

Rating

NPSS thrust rating fraction for updating or de-rating of an engine after design

(1=100 **Re_ des**

Design Reynolds number for the Fan and LPC

Re_ des_ HPC

Reynolds number for the HPC

S_ BypNozz

Bypass Nozzle discharge coefficient scalar

S_ BypNozzCv_ highAlt

Core Nozzle velocity coefficient scalar at high altitude

S_ CoreNozz

Core nozzle discharge coefficient scalar

S_ CoreNozzCang

Core nozzle angular coefficient scalar

SLS_ Thrust

SLS Rated Thrust

TO_ Alt

Take off altitude (feet)

TO_ MN

Take off mach number

TO_ Thrust

Take off thrust

TOC_ Alt

Top of climb altitude (feet)

TOC_ MN

Top of climb mach number

TOC_ Thrust

Top of climb thrust (pounds)

TOC_ Wratio

Mass flow of Top of Climb to Aero Design Point

Inlet_ eRam

Inlet eRam

Inlet_ FlowControl

Bleed flow required for inlet flow control

LPT_ Mn_ out

LPT exit Mach number (sets exit area)

numMainGearTires

Number of tires per strut on main gear

numNoseGearTires

Number of tires per strut on nose gear

HPT_ Bi_ m

Metal Biot Number

HPT_ l_ tbc_ rotor

Thermal barrier coating thermal conductivity

HPT_ n_ cint

Internal cooling efficiency

HPT_ e_ f

Film cooling effectiveness

HPT_ t_ tbc_ rotor

Thermal barrier coating thickness

LPT_ Bi_ m

Metal Biot Number

LPT_ l_ tbc_ rotor

Thermal barrier coating thermal conductivitiy

LPT_ n_ cint

Internal cooling efficiency

LPT_ e_ f

Film cooling effectiveness

LPT_ t_ tbc_ rotor

Thermal barrier coating thickness

HPT_ l_ tbc_ vane

Thermal barrier coating thermal conductivity

HPT_ t_ tbc_ vane

Thermal barrier coating thickness

LPT_ l_ tbc_ vane

Thermal barrier coating thermal conductivity

LPT_ t_ tbc_ vane

Thermal barrier coating thickness

VCTE

variable camber trailing edge scalar

s_ CDft_ wing

scalar for the turbulent skin friction drag on the wing

CooledCoolingNondimensionalWeight

cooled cooling non-dimensional weight

IntercoolerNondimensionalWeight

intercooler non-dimensional weight

TransREWingUpper

turbulent transition Reynolds number for upper wing surface assuming a 20 degree sweep

TransREWingLower

turbulent transition Reynolds number for lower wing surface assuming a 20 degree sweep

TransREHT

turbulent transition Reynolds number for horizontal tail surface assuming a 20 degree sweep

TransREVT

turbulent transition Reynolds number for vertical tail surface assuming a 20 degree sweep

B.4 ANOPP Variables

PER1

Core nozzle chevrons 1=no chevrons, 2= full coverage chevrons

PER2

Bypass nozzle chevrons 1=no chevrons, 2= full coverage chevrons

CORAP

Suppression factor on fan discharge noise

CORTO

Suppression factor on fan discharge noise

DISAP

Suppression factor on fan discharge noise

DISTO

Suppression factor on fan discharge noise

INLAP

Suppression factor on inlet noise

INLTO

Suppression factor on inlet noise

JETTO

Suppression factor on jet noise

LESAP

Suppression factor on leading edge slats

MGRAP

Suppression factor on main landing gear

NGRAP

Suppression factor on nose landing gear

TEWAP

Suppression factor on trailing edge wing

TEFAP

Suppression factor on trailing edge flap

TEFCB

Suppression factor on trailing edge flap

JETAP

Suppression factor on jet noise

LESCB

Suppression factor on leading edge slats

MGRCB

Suppression factor on main landing gear

TEWCB

Suppression factor on trailing edge wing

SWETF

fuselage wetted area scalar

TEFSL

Suppression factor on trailing edge flap

MGRSL

Suppression factor on main landing gear

TEWSL

Suppression factor on trailing edge wing

LESSL

Suppression factor on leading edge slats

APPENDIX C

TECHNOLOGY IDENTIFICATION, EVALUATION, AND SELECTION (TIES) METHODOLOGY

The Technology Identification, Evaluation, and Selection (TIES) methodology was developed by Kirby and Mavris at the Aerospace Systems Design Lab (ASDL). The methodology incorporates aspects of the Technology Impact Forecasting method, but conducts an exploratory assessment of technologies instead of a normative assessment potential impacts required to meet a goal. The TIES methodology has eight main steps: Problem Definition, Define Concept Space, Modeling and Simulation, Design Space Exploration, Determine System Feasibility and Viability, Specify Technology Alternatives, Assess Technology Alternatives, Selection Best Family of Alternatives.

In *Problem Definition*, the objectives for the program are set in terms of metrics and constraints. The metrics and constraints can capture both aspects of performance and aspects of the budget of the entire system. After the goals and constraints of the system have been set, potential vehicle architectures are defined and the key system design variables are identified in *Define Concept Space*. Morphological analysis is utilized to enumerate all of the different system architectures that can be defined. For each architecture of interest, important design variables are identified and potential ranges for each are enumerated. Applying ranges to the design variables enables a probabilistic design space exploration.

The different baseline vehicles defined through the design space exploration must next be analyzed for their performance, which requires a suite of analysis tools. Therefore, in *Modeling and Simulation* the tool requirements are enumerated, tool alternatives are identified, and a final environment is selected. The selected environment must be able to capture the physics relevant to the identified performance metrics.

The selected environment is utilized in the next step, *Design Space Exploration*. Design of Experiment (DOE) techniques are utilized to sample the space created by the design variable ranges, where each case in the DOE is representative of a different baseline vehicle system. The different simulation cases enumerated by the selected DOE are conducted to facilitate the probabilistic vehicle performance analysis. The performance results produced from this analysis enable the selection of a baseline vehicle model that provides the best performance; therefore, the ranges on the design variables do not represent uncertainty. Rather, the ranges are used for a bounding exercise to show the performance that can be achieved by the selected architecture.

The results of the design space exploration are used in the next step, *Determine System Feasibility and Viability*, to determine the need for technology infusion. The probabilistic results are provided in the form of cumulative distribution functions (CDFs), which will provide the probability of success (POS) for meeting the established performance metrics. When the POS is small or zero, technology infusion is required.

Once the need has been established, technology alternatives are defined in *Specify Technology Alternatives*. Kirby utilizes the technology k-factor modeling approach to represent the impacts of the technologies under consideration. Each technology impact, both beneficial and detrimental, are provided in the form of a technology impact matrix (TIM). Row in the TIM represents a different technology and each column is a different k-factor for the modeling environment. The technologies are mapped to each of the k-factors with either no impact, a beneficial impact, or a detrimental impact. Kirby acknowledges that the values and the ranges used in the TIM for each technology are connected to the current technology readiness level (TRL) of the technology, and a technology with a high TRL should be represented by a small amount of uncertainty surrounding its TIM values.

In addition to technology impacts, the compatibility of technologies must also be considered. Within the group of technologies under consideration, there may be technologies that are incompatible with each other. Furthermore, technologies may be incompatible with certain aspects of the system architecture. The incompatibilities are tracked in a technology compatibility matrix (TCM), where a value of -1 represents an incompatible combination.

The next step, *Assess Technology Alternatives*, involves formulating and evaluating technology portfolios. A full factorial analysis of all compatible technology portfolios can be assessed if the computational resources are available. Otherwise, a subset of technology portfolios is formulated based upon the information in the TCM. The TIM is utilized to combine the impacts of each technology within a given portfolio to produce an input vector that represents the entire portfolio. The technology portfolios can then be evaluated deterministically or probabilistically by utilizing the selected modeling and simulation environment. After the portfolio alternatives have been analyzed with respect to performance and cost, the final portfolio is selected in *Selection Best Family of Alternatives*. Several multi-attribute decision making techniques are suggested, such as a genetic algorithm,technology frontiers, and TOPSIS. In some cases an overall evaluation criterion may be required, which involves applying importance weights to the performance goals. Furthermore, the robustness of each of the alternative portfolios with respect to different weighting scenarios can be assessed to determine the best overall technology portfolio.

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A Quantitative, Model-Driven Approach to Technology Selection and Development through Epistemic Uncertainty Reduction

Katherine N. Gatian

399 Pages

Directed by Professor Dimitri Mavris

When aggressive aircraft performance goals are set, he integration of new, advanced technologies into next generation aircraft concepts is required to bridge the gap between current capabilities and required capabilities. A large number of technologies exists that can be pursued, and only a subset may practically be selected to reach the chosen objectives. Additionally, the appropriate numerical and physical experimentation must be identified to further develop the selected technologies. These decisions must be made under a large amount of uncertainty because developing technologies introduce phenomena that have not been previously characterized. Traditionally, technology selection decisions are made based off deterministic performance assessments that do not capture the uncertainty of the technology impacts. Model-driven environments and new, advanced uncertainty quantification techniques provide the ability to characterize technology impact uncertainties and pinpoint how they are driving the system performance, which will aid technology selection decisions. Moreover, the probabilistic assessments can be used to plan experimentation that facilitates uncertainty reduction by targeting uncertainty sources with large performance impacts.

The thesis formulates and implements a process that allows for risk-informed decision making throughout technology development. It focuses on quantifying technology readiness risk and performance risk by synthesizing quantitative, probabilistic performance information with qualitative readiness assessments. The Quantitative Uncertainty Modeling, Management, and Mitigation (QuantUM^3) methodology was tested through the use of an environmentally-motivated aircraft design case study

based upon NASAs Environmentally Responsible Aviation (ERA) technology development program. A physics-based aircraft design environment was created that has the ability to provide quantitative system-level performance assessments and was employed to model the technology impacts as probability distributions to facilitate the development of an overall process required to enable risk-informed technology and experimentation decisions. The outcome of the experimental efforts was a detailed outline of the entire methodology and a confirmation that the methodology enables risk-informed technology development decisions with respect to both readiness risk and performance risk. Furthermore, a new process for communicating technology readiness through morphological analysis was created as well as an experiment design process that utilizes the readiness information and quantitative uncertainty analysis to simultaneously increase readiness and decrease technology performance uncertainty.