THE ENERGY DELIVERY

PARADIGM

BY

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"The Energy Delivery Paradigm", a dissertation prepared by Stephen Arthur Bukowski in partial fulfillment of the requirements for the degree, Doctor of Philosophy, Engineering specialization in Electrical Engineering has been approved and accepted by the following:

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I chose a more difficult path to obtaining my PhD by returning to academics after 20 years of industry work and a move from MT to NM with six children. Each of my children may not understand what they experienced immediately, but my wife and I hope that if and when they attend college, they can remember back to the experience they lived through with us. There are several people in my life that have been instrumental influencing me in my pursuit of my PhD. Influence has come in many forms including encouragement, moral support, academic help, career advisement, philosophical discussions, financial support, advisory recommendations, and friendship. My initial desire for a PhD was inspired by my mom and dad. I was raised in an academic environment as my father was a Professor of Mathematics and my mother's desire to travel all over the word provided jobs from the Saudi Arabia to Alaska. As a kid I remember my dad telling me, that if I enjoyed math I should become and engineer and not a mathematician. When I arrived at the University of New Mexico for my undergraduate in the late 80's, Dr. Chaouki Abdallah had significant impact on my undergraduate engineering degree and was key in providing me an opportunity for my MSEE PhD program. He has been a keen influence and mentor throughout my academic career. Upon returning to my PhD program I thought it was

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ABSTRACT

THE ENERGY DELIVERY
PARADIGM

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A sustainable world is one in which human needs are met equitably without harm to the environment, and without sacrificing the ability of future generations to meet their needs. Electrical energy is one such need, but neither the production nor the utilization are equitable or harmless. Growth of electricity availability and how we use electricity in industrialized nations has established a dichotomy between usage and sustainability. This dichotomy is best illuminated by the current "just-in-time" approach where excessive electricity generation capacity is installed to be able to instantaneously meet load from consumers at all times. Today in the United States, electricity generation capacity is approximately 3.73 kW per person versus 3.15 kW per person in 2002. [1] [2] At this magnitude of installed capacity the entire world would need approximately 25.5 TW of generation or approximately 12,250 Hoover

Dams today and must add 766 MW of capacity every day. [3] This unsustainable effect is further exacerbated by the fact that consumers do not have a strong vested incentive to keep electricity generation sustainable because the producers shoulder the burden of instantaneously meeting demand.

What is needed are paradigms to make these resources economically sustainable. The opportunity provided by the smart-grid is lost if we just automate existing paradigms, hence it is new paradigms that should be enabled by the smart-grid. This dissertation examines a new paradigm which shifts the problem towards 'energy delivery' rather than 'power delivery' for economic sustainability. The shift from a just in time power model to an energy delivery represents a fundamental change in approach to the research happening today.

The energy delivery paradigm introduces the concept of a producer providing electrical energy to a system at a negotiated cost and within power limits, leaving the issue of balancing instantaneous power to the consumer, which has overall control on its demand and power requirements. This paradigm has potential to alter the current technical, market, and regulatory problem in electrical energy production and move the economic landscape toward electrical energy production for a more sustainable, reliable, and efficient electrical energy system. This dissertation examines concepts along the path of energy delivery which crosses many fields including power systems, data communications, controls, electric markets, and public utility regulation ultimately proposing a mathematical formulation and solution. The dissertation then shifts to examining potential physical interpretations of the formulation and solution and impacts to different fields within the energy paradigm.

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ABBREVIATIONS

Pg_i - the power output level at bus_i during any time period.

Pd_i - the demand at bus_i during any time period.

λ - Lagrangian multiplier associated with the transmission line constraint

cp - matrix in the algorithm identifying each λ for every transmission line

dv - matrix of constraint error for each transmission line

μ - Lagrangian multiplier associated with energy constraints

mu - matrix in the algorithm identifying each μ for every bus

ev - matrix of constraint error for energy requirement at bus_i

γ - Lagrangian multiplier associated with the transmission line capacity constraint

cq - matrix in the algorithm identifying each γ for every transmission line

qv - matrix of constraint error for each transmission line capacity

sbXY the local sub-problem at time period (X) and bus (Y)

gCost - the generation preference/cost at the bus as a function of Pg_i

dCost - the demand preference/cost at the bus as a function of Pd_i

kW – kilowatt

kWh – kilowatt-hour

M - the original objective function when representing the new Lagrangian

TL_k - transmission line k

General Notation:

XbYtp – X is the number of **b**uses and Y is the number of **t**ime **p**eriods. ...

X_i^j - variable X at bus ***i*** and time period ***j*** (note bus is located subscript and time period is superscript).

Example: $(t^1_{12} + t^1_{21}) = Pg_1^1 + Pg_2^1 - (Pd_1^1 + Load_1) = 0$. Here t_{12}^1 represents the transmission line power between bus 1 and 2 during time period 1, while E_i represents and energy constraint for bus ***i*** which does not correspond to a time period.

INTRODUCTION

There is extensive literature describing the on-going evolution of the electric power industry resulting from a multitude of factors within the global and national economies and political arenas. Some of those factors include: deployment of distributed and renewable energies, electric vehicles, and demand response, as well as deregulation of electric utilities, power flow congestion and ageing infrastructure, security risks, limited resources, and ultimately climate change and sustainability. Each of these factors contributes to moving the electric power industry away from the legacy model toward a new model often termed "the Smart Grid". This is resonated in FERC's Smart Grid Policy which outlines 4 key grid functionalities, situational awareness, demand response, electric storage, and electric transportation. [4] The Smart Grid is an overarching concept helping define a path for an emerging industry. It is believed that the confluence of the "Smart Grid" concept, advanced research, and technology growth can develop a sustainable energy delivery system. This dissertation examines aspects of the shift from just-in-time power delivery paradigm to an energy delivery paradigm. – an approach where a specific amount of energy is supplied over a specific time interval. This shift from a just-in-time power model to an energy delivery model represents a fundamental change in approach to the research currently ongoing.

This paradigm:

- Enables new markets by altering the existing market for electrical energy delivery and shifting the instantaneous power to the consumer.
- Motivates and includes the consumer: Interaction between producer and consumer creates awareness, benefits, and information for consumers
- Builds upon the foundation premise of a network to provide services and open access
- Enables more efficient energy production for generating units
- Integrates communication and energy delivery for more sustainable and dynamic electric energy system
- Reduce and defers new generation costs by free existing capacity for energy delivery
- Creates reduced investment risk for generation
- Improves reliability and security

Fundamentally this concept disrupts the classical approach to the electric power system and markets by providing a new window into solving the electrical energy needs of customers moving us closer to what the National Energy Technology Laboratory calls a "modern grid". [5]

This dissertation illuminates the concepts critical to the path of energy delivery and provides an overview of the areas for proposed research which crosses many fields including power systems, data communications, controls, electric markets, and public regulation.

Following is the output of an electrical generator that matches the instantaneous power requirements of users. The generator ramps up and down to maintain balance of apparent power. The generator shifts through different utilization and efficiency points to meet the varying demand.

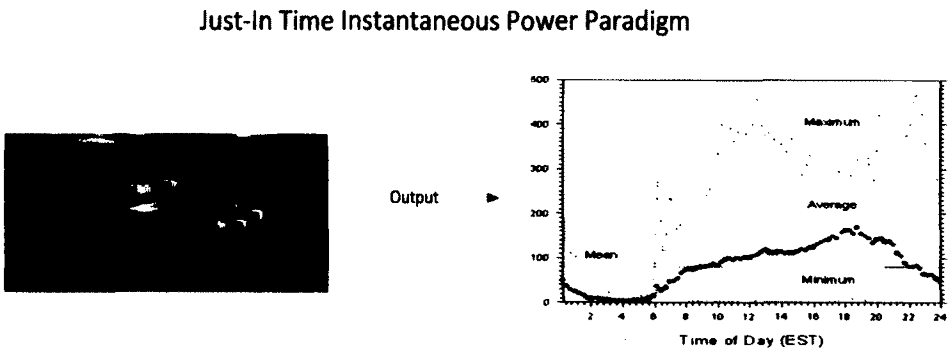

Figure 1: Instantaneous Power Delivery

In comparison, the energy delivery paradigm provides the opportunity for generators to run at higher efficiency levels and flattens the demand curve, as seen in Figure 2. The concepts in this dissertation applies to any power system, however is easily enabled by using microgrids as a vehicle towards realizing an energy delivery system. Today microgrids are being built to support diverse objectives and are adding control and awareness by integrating more and more devices with embedded communications and new capabilities. Within the energy delivery vision microgrids are seen as cyber-physical systems consisting of both distributed energy sources and energy demands with differentiated reliability expectations, shifting the way we use and build today's power systems to energy systems. Microgrids provide a stage for separating the issues of supplying electrical energy and the local instantaneous power requirements of demand. The energy paradigm offers a different load curve to producers, essentially flattening or creating a more grid-friendly load curve. The vision further extends the microgrid to participate in communications and energy flow between other microgrids, ultimately creating new services and opportunities.

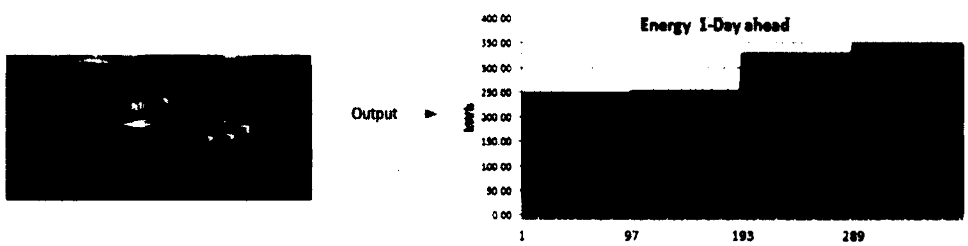

Figure 2: Energy Delivery

The application domain for the energy delivery paradigm is a customer-driven microgrid - a utility distribution feeder in which customers invest in resources and the utility becomes an "enabler" for reliable energy transfers. The customer-driven microgrid integrally ties together the utility, distributed generation, storage, operation and control, and market and economic participation of the consumer for energy services. Different from today's implementation of centrally controlled microgrids, where all devices typically have a common ownership and support a global objective, the customer-driven microgrid requires the individual objectives of participants in its energy delivery. This aspect of the customer-driven microgrid encapsulates the dynamic load participation and differentiate reliability aspects essential in the Smart Grid vision. As more embedded systems become routine in our lives it is easy to foresee the customer-driven microgrid representing the electricity grid of the future. Thus the goal of the research is to begin to investigate and provide the scientific insights necessary to enable an energy delivery future.

The dissertation is broken into several sections. The first section lays out the background and motivation of the energy paradigm. It illustrates a dichotomy between usage and capacity and illuminates research, policy, and trends of the electric industry today. The next section builds the formulation of energy delivery and identifying actors and concepts defining roles. A global minimization problem is formulated and presented relating to the actors and concepts. Following the formulation a methodology of solving the formulation via the algorithm is presented and explained. The sections following this develop the aspects and characteristics of the algorithm and relate their relationship to the formulation and methodology presented. Several examples are offered representing key aspects and interactions of the algorithm and results. An IEEE 13 bus test case is used to demonstrate practicality as well as highlight aspects of the algorithm that are key to the energy paradigm. Finally additional possibilities such as market functioning and capacity constraints are examined with the algorithm.

BACKGROUND

The primary goal of this section is to provide the motivation and background to the energy delivery paradigm. The motivation is derived from several aspects including: sustainability, federal regulation, evolving markets, and advancement in agent/cyber-physical research, embedded systems, storage, and distributed generation.

It is argued that the primary function of an electrical power system is to deliver electrical energy to customers. Thus it is prudent to consider the underlying reliability and usage implication to the original "just-in time" power paradigm versus the energy paradigm. Two questions that help initiate the energy delivery paradigm are: "Would the development of consumer awareness and action about capacity alter usage behaviors and needs ultimately changing how we produce electrical energy?" and "does every consumer need or want the reliability level the electric utility currently provides?"

A primary motive for investigation into an energy paradigm is sustainability and efficiency. Based on the 3.73 kW of installed capacity per person in the US, each unit of capacity could on average sits idle for approximately 55% of the time and still produce the amount of electrical energy consumed in the U.S. [6] This author argues that consumer participation in the solution is a key to achieve sustainability and efficiency of electric energy use. Solving the dichotomy of usage (consumer) and implication to service (producer) is critical in the path to sustainability. The author believes that consumer participation is not the actual consumer providing the interaction in its energy usage, but a software agent representing the consumers' needs which can manage resources of the consumer in a method "learned" or preferred by the consumer. Just as we see "learning" thermostats which provide improved efficiency for the consumer while meeting the consumers temperature comfort needs; we would have an electrical energy agent that works on the consumer's behalf in the electrical energy paradigm. The consumer's agent is a critical component of the energy delivery paradigm.

Type, quantity, and characteristics of electrical devices have changed considerably over the last 25 years as intelligence has begun to enter most devices. Whether it is commercial, industrial, or residential, electrical devices have become more controllable and sport processors for interface, control, and monitoring. The wave of devices with embedded computing capability is upon us. This represents a different type of electrical load from the electrical load that was present for the building of the current power system. Having the embedded systems on the devices represents a significant step toward developing information and control linking to the overall characteristics of the demand and energy. These devices will be able to participate in developing demand preference functions and energy constraints for the consumer. For example, the NEST thermostat which has embedded systems interacting with the desires of the consumer and control of a large electrical load, the foundation of a demand preference functions or an electric vehicle which requires a quick charge or a less constrained energy requirement to reach 90% over 8 hours.

This discussion is not narrowed to a particular type of demand or customer. The discussion represents a concept that all devices will have the embedded processing and memory to provide information and control that was not available or quantifiable before. The Energy Delivery paradigm is about building a more efficient and robust electrical energy system based upon preferences which are derived from information available from the end users.

The Energy Delivery paradigm has significant potential to flatten the demand curve as well as utilizing energy usage information to project and predict energy requirements. Ultimately this can provide the opportunity to free up existing capacity, deferring new costs along with allowing energy delivery at higher efficiencies further reducing costs. Additionally the current metric for capacity utilization represents a hurdle for investment into generation. The significant potential for idle assets represents risk to the investor and potential investors, hence any reduction of this risk could allow for more incentive to investors and incentive to invest. Many of these benefits have been examined by PNNL where demand side flattening has been given monetized values; however the concept originates from a different motivation. [7] Overall the reduction of capacity needs represent a fertile area to investigate efficiencies and sustainability questions and is a primary motivation to re-examine the fundamental issue of responsibility and expectations for meeting instantaneous power.

Initial framework and support for the network to support an energy delivery paradigm has already been established. In 1996 FERC introduced Order 888 as an attempt to remove impediments to completion in the wholesale bulk power marketplace with intentions to bring more efficient, lower cost power to the U.S. consumers, essentially laying the necessary foundation for a competitive wholesale energy markets via open access for transmission. [8] This enabled some of the traditional vertically integrated utilities to begin to shift their business and market focus while also creating new markets and allowing new providers entry into existing markets. This was followed by FERC Order 2000 in 2000, where FERC introduced further guidance for formation of ISO/RTO's for operation and control of regional areas to increase reliabilities and efficiencies of the transmission system as competitive markets developed. In addition to addressing reliability issues effectively and internalizing loop flow caused by the growing number of transactions from wholesale energy markets, FERC 2000 identified the need for large regional control authorities to exist to facilitate transmission access across larger networks, improving market efficiencies and promoting further competition by eliminating the pancaking of transmission rates resulting in a greater range of economic energy trades across the network. [9] This proposal argues that Order 888 and Order 2000 represent significant steps toward developing a core energy delivery system by unbundling services for competition and creating a network for service delivery and markets in support of the core function of energy delivery.

Electricity deregulation or electric market restructuring has been on the forefront of discussions, legislation, and experiment for many years. This shift in the electrical market follows the successful deregulation of the telecommunications industry, which underwent significant change to open up to competition and new services. There are supporters on both sides of the issues of either staying the course of a public, private, government partnerships or moving to a competitive open market. Each side advocated for lower costs, reliability, and efficiencies with the deregulation supporters emphasizing the potential for innovation, new markets, and open competition. Clear support for a comprehensive legislative act from Congress has been slow and murky for many reasons including contention on methodology, State or FERC oversight authority, and the flood of political money from both sides to both parties. Given the lack of a comprehensive legislative act, parts of the US have been taking steps towards deregulation with mixed results and outcomes creating further lag in the legislative initiatives. Support of an energy delivery system must be provided by the regulatory bodies.

Leading the evolving markets for energy services outside of standard ancillary services are the demand response programs being implemented by utilities and ISO/RTO's. The overall approach to demand response initially has been for stability and reliability issues for different levels of control and commitment from producers and consumers. Programs like Open Automated Demand Response (OADR) represent the beginnings of initiating interaction with consumers and consumer's demand to create new markets by enabling customer participation. [10] The customer demand characteristics represent the largest control opportunity for the electrical system and as this proposal argues is the core cause of excess capacity. Demand response is a solid example of an energy service beginning to take shape illustrating the core requirement of an energy delivery paradigm, a network delivering services.

A further area in motivation comes from the research areas in agents, embedded systems, storage, and distributed generation. These areas are of special interest and each play a role in the Smart Grid vision; however it is the convergence of these areas in a microgrid that provides an opportunity to shift the traditional paradigm to energy delivery. Agent research, embedded systems, and Cyber-physical systems are converging upon a common direction and definition. This common basis can be described as: a software (and/or hardware) entity that can autonomously react to its environment; [11] [12] or a system which integrates computing, communications, and control with the natural world. [13] [14] This common basis forms a foundation for research into systems that can be built and integrated with storage and distributed generation systems of systems to provide the functionality necessary at the customer level to participate in an energy delivery paradigm, ultimately enabling the shift of responsibility of meeting instantaneous power to the consumer and energy delivery to the producer.

The last area of motivation and support of the energy concept is the progress within FENIX (Flexible Electricity Networks to Integrate the eXpected "energy evolution") funded by the EU under the sixth and seventh Framework Programme. The seventh Framework Programme has many goals, one of which is the developing of a microgrid reference architecture based upon microgrid scenarios, business cases and uses cases; note that a similar initiative is currently being funded by the DOE with participation of all the US national labs (SNL, LANL, PNNL, LBNL). The EU project contrasts the aggregation of capacity by a Virtual Power Plant to a microgrid which is generally intended to balance supply and demand. [15] These concepts represent the fundamental basis of the energy paradigm. It identifies the commonalities of the VPP's and microgrids and recognizes the functional separation of energy toward the network and instantaneous power locally.

PROBLEM FORMULATION

The energy delivery paradigm represents a shift away from traditional electrical power model where the responsibility of meeting all instantaneous power requirements falls only to the utility or producers. In an energy delivery paradigm the responsibility of meeting instantaneous demand shifts from the utility to the consumer and the utility and other participants become energy delivery entities. The essential question that needs examined is how does the energy delivery paradigm work? The author does not envision that one day every customer begins requesting energy from the utility, nor is every customer capable of managing their own instantaneous power today. However this author believes that the collective indicators mentioned above (policy, workings of whole markets, needs for ancillary services, capacity conditions, expansion of embedded systems) that when examined as a whole demonstrates a potential shift in how we use electrical energy. The energy delivery paradigm application space is not limited to the microgrid concept. The formulation presented in this section can be applied to many electrical energy power problems. One example could be determining optimal charging and usage of an electric vehicle fleet against a time of use demand and energy tariffs or incorporating demand response or the interaction of different generation types which operate different preference/cost functions such as solar versus fuel based source. The concept of production and consumption preferences (generation or demand) over different time intervals introduced in the formulation are applicable in many applications as they represent concepts of supply and demand which has numerous applications in many fields. Overall the energy delivery formulation represents the interaction of local preference functions and a global objective, and the formulation presented is narrowed with a specific minimization and specific constraints.

To take the first step in developing a frame of reference to the energy delivery paradigm we present the concept of a microgrid in multiple steps. The microgrid concept presents a vehicle to represent characteristics and function of actors of the energy delivery paradigm, ultimately allowing a mathematical formulation based upon concepts that have been used by utilities. Defining the concept of microgrid is important, as when this dissertation was being written, the term microgrid was used in many different circles with several different meanings and usages and continues to evolve. The term microgrid originates as way to describing the concept of a small power system without interconnection to a larger system of interconnected systems. The concept of a microgrid has origins to the first electrical systems, but the word seems to have evolved as necessity later as a contrast to the larger interconnected power system, not with the evolution of the first power systems. Below is a set of definitions which is not all inclusive but establishes a solid set of concepts presented within industry, research, and government agencies at this time.

Microgrid definitions:

1. A collection of small generators for a collection of users in close proximity. [16]

2. Operation of distributed generators serving separate loads via a non-utility electrical distribution system in a coordinated arrangement offering higher reliability to a multiple facility (load) site. [17]
3. A network of micro-sources and storage devices that can operate in both grid-connected and islanded modes. [18]
4. The organizing of distributed energy resources to meet electrical needs of customers. [19]
5. An integrated energy system consisting of distributed energy resources and multiple electrical loads operating as a single, autonomous grid either in parallel to or "islanded: from the existing utility power grid. [20]
6. Independent electrical generation and distribution systems which deliver energy that is reliable, economical, and sustainable. [21]
7. A group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode. [22] [23]
8. A part of the electrical power distribution network with: multiple DER, loads, and the capability of islanding and operating independently from the grid. [24]
9. A grouping of interconnected loads and distributed energy resources that can operated in both island mode or grid-connected and acts as a single controllable entity to the grid. [25] [26]

10. A small power system composed of one or more distributed generation units that can be operated independently from the bulk power system. [27]
11. A power system with distributed resources serving one or more customers that can operate as an independent electrical island from the bulk power system. [28]
12. Small power systems of several MW or less in scale with tree primary characteristics: distributed generators with optional storage capacity, autonomous load centers, and the capability to operate interconnected with or islanded from a larger grid [29]
13. An integrated system consisting of interconnected loads and distributed energy resources which operate as an integrated system either in parallel to or "islanded" from the existing utility power grid. [30]
14. A localized grouping of distributed electricity sources, loads, and storage mechanisms which can operate both as part of the central grid or independently as an island. [31]
15. A μGrid is a semiautonomous grouping of generating sources and end-use sinks that are placed and operated for the benefit of its members, which may be one utility "customer," a grouping of several sites, or dispersed sites that nonetheless operate in a coordinated fashion. [32]

Taking the characteristics and objectives shared within the definitions provide the basis for the definition used in this dissertation.

Defining Characteristics

1. Collection of loads, generators, storage, micro-sources, distributed energy resources, or devices (Cyber-Physical-Devices).
2. Organizing / Operate autonomously / single controllable entity with respect to grid / customer serving
3. Interconnected / connected / disconnected (islanded)
4. Collection of devices creating a single controllable system; collection of systems creating a single controllable larger system
5. Single objective (directed strategy) and N-objectives

Defining Objectives

1. Supply and delivery of electrical energy, supply and delivery of electrical power
2. Sustainable, reliable, economical, efficient – Reliability and Efficiency

For the initial step of the problem, a simple definition is presented and built upon as the model and additional concepts are introduced. For illustration of the first concept, the microgrid is defined a collection of electrically connected assets individually or collectively owned that consume, produce, and/or store electrical energy.

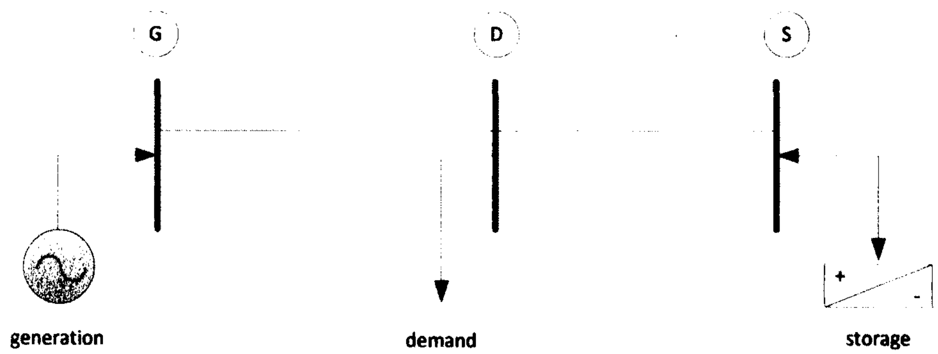

Figure 3: Simple Microgrid

Assets or more precisely, energy assets are described as any object that could participate in the electrical systems. Examples include any type of demand, generation, or storage. Storage can be considered an asset with has both demand and generation characteristics. Extending the concept is that each object can be any combination of demand, generation, or storage and can have 1 to N ownership preferences as shown in Figure 4 below.

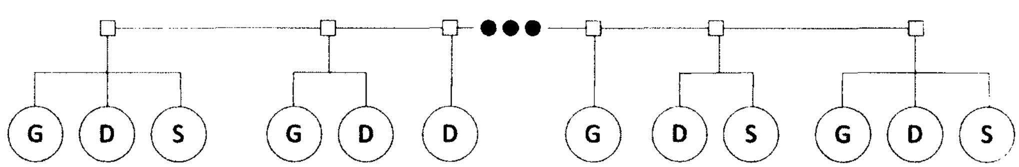

Figure 4: 1 to N system

Again, extending our definition of the microgrid, demand can have temporal characteristic where it can be deferred or scheduled, and it can also vary over time.

Generation can be any form of electric energy generation such a diesel generator, solar installation, fuel cell, wind generator, etc.; distributed or centrally located as in a utility actor, or both. And finally, storage represents a unique combination of demand and generation with potential temporal characteristics. Just as demand and generation may have unlimited types of preferences, storage has that similar characteristic, as a fixed asset may act an electric vehicle battery dictating a certain SOC at a specific time. Overall the formulation must take into account the generation, demand, and storage preferences of all assets based upon all available factors of the assets which includes ownership.

Individual ownership of attached devices within the microgrid represents an inevitable next step for microgrids. Today microgrids are built under a single ownership such as a military installation, university campus, or industrial operation. The dynamics and motivation of participants change when each participant acts on their individual objectives. Examples of preferences are introduced later and represent a critical link in bridging the physical and mathematical worlds.

Continuing to update our microgrid definition, a microgrid's primary function is to participate in the delivery of electrical energy and that each entity can be logically represented by an agent. The agent has the responsibility to decouple the instantaneous power requirements of the local area from the energy needs of the network. Generally speaking the agent is also responsible for implementing the preferences of the electrical assets for which it is associated. From the network side, the agent negotiates energy delivery for each time period with other agents and on the local side the agent utilizes and manages local resources to meet instantaneous power requirements. Figure 5 represents the logical overview of the agent. This dissertation utilizes the same functionality and definition for an agent and cyber-physical device. Both describe a combination of hardware and software that can act on its environment, hence they are used interchangeably within this dissertation.

Again extending our microgrid definition, a microgrid is a collection of cyber-physical device electrically connected that produce and/or consume electrical energy possibly based upon a global objective and where each entity may have time-varying individual objectives and the collection can be viewed as a single equivalent system with potential to interconnect to other systems. From this description the agent or cyber-physical device can have properties of a consumer, producer, or both; sometimes called a "prosumer". The agent is responsible for an objective function for

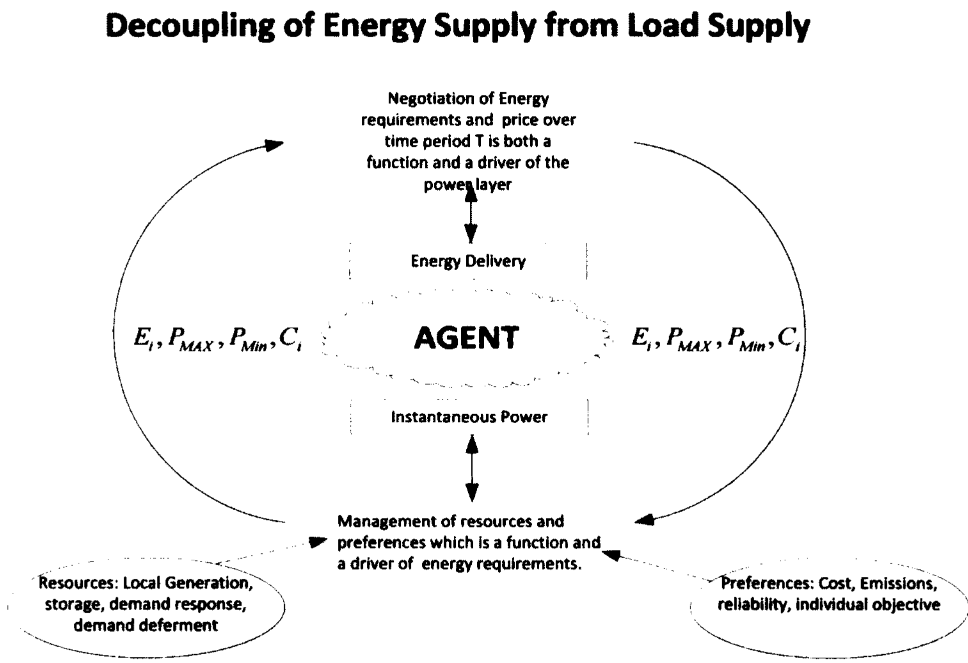

Figure 5: Decoupling of the Energy Supply from Load Supply

the network and the local area, one for energy delivery and one for instantaneous power delivery based upon preferences of the owner and operation of electrical assets. Figure 6 shows the agents function in participating in local and global optimization. The agent of cyber-physical device becomes a center piece of the energy delivery paradigm. Its role is to act on a set of preferences or requirements, learned or programed, to satisfy the energy needs of the local system and support of the network. In general preferences and requirements are derived from the energy assets (demand, generation, storage, etc.) and individual preferences. Individual preferences can include any type of motivation such as economic, environmental, political, or social goals.

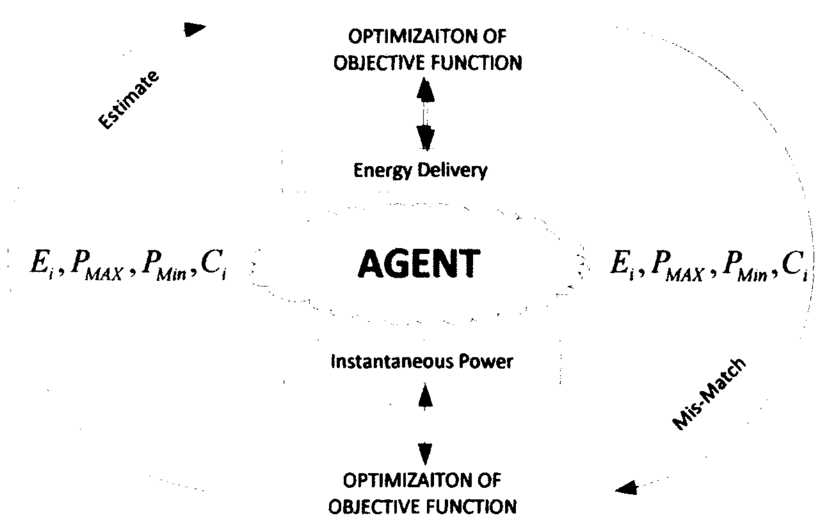

Figure 6: Optimization of Local and Network sides

Preferences and requirements derived for generation can be based upon factors that related to generation type, fuel, resources, environment, or commitments. Similarly demand preferences can be derived based upon demand characteristics such as demand type (controllable, deferrable, varying over time), commitments (critical, non-critical), environmental, and economical. Storage is an important factor for the energy delivery system. Integration of storage as a resource to the agent provides an important component to mitigating problems with instantaneous demand. As electric and hybrid vehicles continue become more ubiquitous, significant energy storage resources may become more available via electric and hybrid vehicles driving the battery industry to develop longer lifetime and lower cost energy storage options. Storage can be presented as a form of generation and demand. It can be used to mitigate instantaneous mismatches in energy being delivered and power needed locally, either in storing excess or providing supplemental energy. Storage can be influenced by individual preferences, commitments, and state of charge.

Previous work in global optimization within a Customer Driven Microgrid has examined centralized and distributed optimization techniques upon minimizing costs of a global objective function during a single instant of time. [33] The customer is equivalent to the producer, consumer, or prosumer; essentially a participant in the power system with electrical assets and preferences. This objective function is a minimization of cost and is based upon the instantaneous requirements of a power system and examines a single instant in time with system constraints. The formulation has roots in power flow and dispatch algorithms used in utilities today, where cost are minimized and power flow is optimized at a single instant of time. Using a simple 2 bus model (Figure 7) with just a single generator and a single demand, the formulation can be represented as:

Minimize $f(P_g, P_d) = G_{cost-pref}(P_g) + D_{cost-pref}(P_d) + Cost_{Global}(P_g, P_d)$ **Equation 1**

Subject to:

$$P_g = P_d$$
$$P_g \leq P_{g_{max}}$$
$$P_d \leq P_{d_{max}}$$

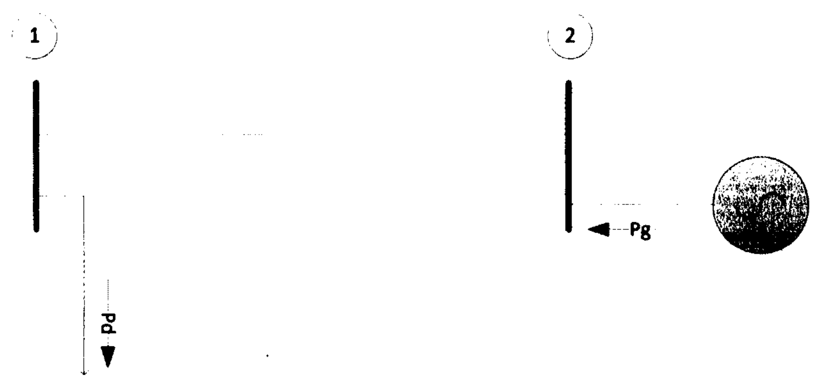

Figure 7: Single Instant of Time - 2 Bus

In this formulation $G_{cost-pref}(P_g)$ represents the output of a generator based upon its preference and similarly, $D_{cost-pref}(P_d)$ is the demand preference. As we consider this model developed within the framework of the microgrid, storage becomes a consideration in the model. The temporal characteristics of storage more closely represents the consumers use of electrical power, which is effectively power over time. A motor is not operated at a single instant of time, nor does an air-conditioner function at a single instant of time, but each operates over time and uses electrical energy. Hence we naturally extend the formulation as a sum of N time periods which can be considered any time duration Δt. Adapting this concept to the diagram, we now see P_d is represented by N time periods or is equivalently P_d^n where n is a value from 1 to N. Adding the effect of storage, we can now establish that a certain state of charge (SOC) is request for the battery resulting in: $P_d^1 + P_d^2 + \cdots + P_d^n = E$. This formulation does not exclude any type of demand or generation from taking on this characteristic, in fact as shown later can be seen as a product of the formulation. For a simple 2 bus system with 2 time periods the diagrams are:

For the first time period:

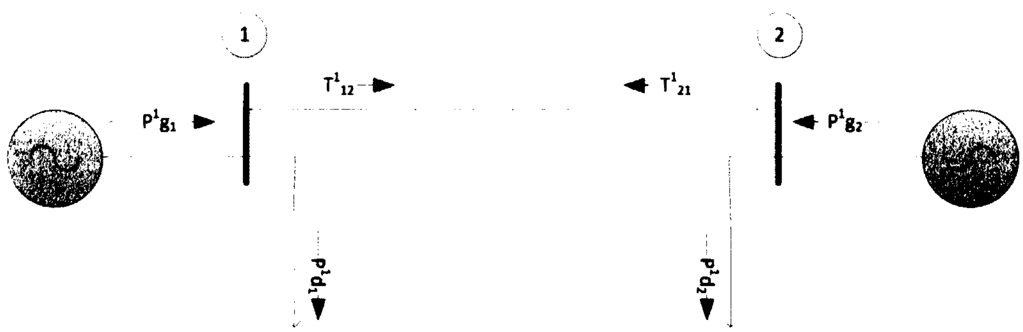

Figure 8: 2 Bus Time Period 1

For the second time period:

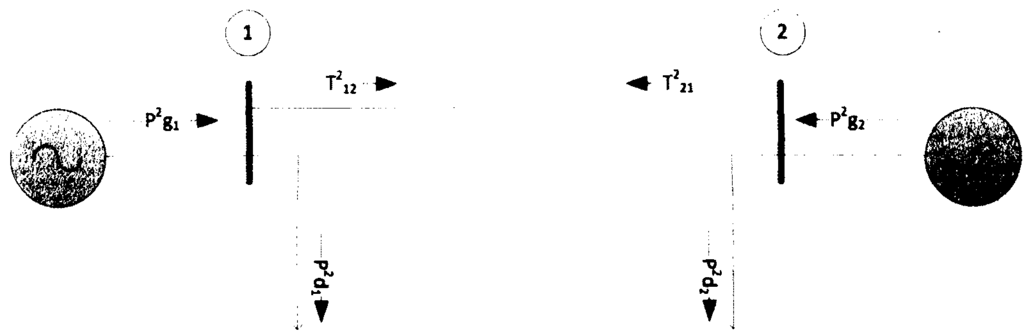

Figure 9: 2 Bus Time Period 2

For Extending to an N time period and M bus systems the formulation is presented as:

$$\text{Minimize } \sum_{T=1}^{n} f^T(P_{g_i}, P_{d_i}) = \sum_{T=1}^{n}\left[\sum_{i=1}^{m} G^T{}_{CP_i}(P_{g_i}) + \sum_{i=1}^{m} D^T{}_{CP_i}(P_{d_i})\right] \quad \textbf{Equation 2}$$

Subject to:

$$P^T{}_{g_i} - P^T{}_{d_i} - t^T{}_{ij} = 0$$
$$t^T{}_{ij} + t^T{}_{ji} = 0$$
$$P^T{}_{g_i} \le P^T{}_{g_i\,\max}$$
$$P^T{}_{d_i} \le P^T{}_{d_i\,\max}$$

With the addition of the energy constraint

$$\sum_{T=1}^{n} P^T_{d_i} = E_i$$ (E_i is the energy required for the time period T by the agent.) **Equation 3**

The global objective function contains customer generation preferences and customer load preferences, where all the participants work to satisfy their local goals as well as work in cooperation with other participants to satisfy the global goal of minimizing system cost. Overall the problem presents the operation of the microgrid via cyber-physical devices or agents communicating and participating based upon preference functions within the physical constraints of the system. This is orthogonal to the current implementation of a power system, where the preference of load and generation do not exist and each node appears as an aggregate of their individual load and generation, which results in the utility responding to instantaneous power requirements.

On a side note for the formulation, it should be apparent that the consideration of generation and demand preferences are not necessary descriptors as the physics of the system automatically implements demand $P_{d_m}^n$ as a negative value and $P_{g_m}^n$ as a positive value. The formulation can be extended to each agent with preference/cost function participates where a positive value in the agents function represents generation and a negative value represents demand. However, to provide a more classical illustration for all readers, the concept of generation and demand help provide the energy situation. Additionally generation and demand preferences are discussed later.

To provide some clarity on the units used in the formulation, preference functions are represented by $/hr in the vertical axis and kW in the horizontal axis. This aligns with classical optimization used by utilities today. This asks the question of units for the system. Pg_i and Pd_i are represented in kW (kilowatts) which is a result from preference functions, however each time period can be in any measure of time. If the time period is considered to be small the problem approach an instant of time and units of kW are valid. However in this formulation units of $kW\Delta t$ are valid for Pg_i and Pd_i as the formulation examines n time periods. Within this document, both kW and $kW\Delta t$ are used depending on the reference and hopefully not confusing the reader.

OPTIMIZATION VIA LAGRANGIAN RELAXATION

To examine the optimization problem, this dissertation examines an approach of Lagrangian relaxation for solving the optimization and the effect of Lagrangian multipliers within the microgrid control. Obviously Lagrangian relaxation is not the only type of optimization; however it provides some enlightening insight to what can be communicated in the operation of the microgrid. In fact it is important to note that during the initial investigation of the Lagrangian optimization technique, an approach was developed that gave some insight to the system as a whole, which, in fact, hid many interesting interactions of the sub-problem maximization. Ultimately it was the sub-problem analysis that shed light into the interpretation of Lagrangian multipliers for control and operation of the microgrid. It is the ability to utilize today's computing power for solving the sub-problem that provides the insight. Within the software written in Matlab for the relaxation formulation, every possible demand and generation level are examined for every bus hundreds or even thousands of times as the Lagrangian multipliers are computed while trying to meet the constraints.

To begin the explanation of the application of Lagrangian relaxation, it is important to represent a classical Lagrangian approach in the simplified formulation to illustrate some key concepts.

To reduce the number of variables we consider a 2 bus system with 2 time periods (n=m=2, 2b2tp) with a single fixed demand on bus 2. From the formulation in Eq-2 becomes:

Minimize $M = \sum_{T=1}^{2}\left[\sum_{i=1}^{2} G^{T}{}_{CP_i}(P_{g_i}) + \sum_{i=1}^{2} D^{T}{}_{CP_i}(P_{d_i})\right] =$

$$G^1_{CP_1}(P_{g_1}) + G^1_{CP_1}(P_{g_2}) + D^1_{CP_1}(P_{d_1}) + G^2_{CP_1}(P_{g_1}) + G^2_{CP_1}(P_{g_2}) + D^2_{CP_1}(P_{d_1})$$ **Equation 3**

Subject to:

Time Period 1:

$Pg^1_1 + Pd^1_1 - t^1{}_{12} = 0$

$Pg^1_2 + Pd^1_2 - t^1{}_{21} = 0$

$t^1{}_{12} + t^1{}_{21} = 0$

Time Period 2:

$Pg^2_1 + Pd^2_1 - t^2{}_{12} = 0$

$Pg^2_2 + Pd^2_2 - t^2{}_{21} = 0$

$t^2{}_{12} + t^2{}_{21} = 0$

With energy constraint: $Pd^1_1 + Pd^2_1 = E_1$. Even in the simplest case notation can be extensive and confusing. To best illustrate the problem sometimes notation is adapted to best communicate and identify the issue. (Note: Pd^1_2 and Pd^2_2 are fixed values $Load_1$ and $Load_2$)

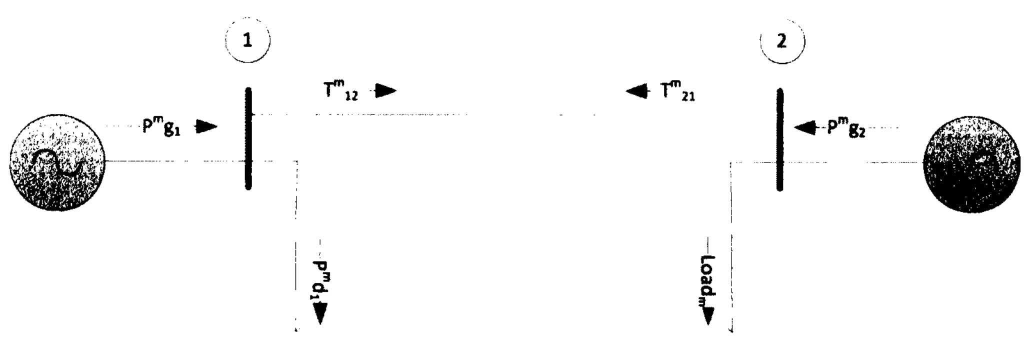

Figure 10: 2b2TP --: 2 bus with m=2

The Lagrangian (L) is found by adding each of the constraints, which have been summed to zero multiplied by its associated Lagrangian multiplier to the global equation. Establishing the Lagrangian (L) we have:

$$L = M + \lambda_1(t^1{}_{12} + t^1{}_{21}) + \lambda_2(t^2{}_{12} + t^2{}_{21}) + \mu_1(Pd_1^1 + Pd_1^2 - E_1)$$

The system Lagrangian consists of Lagrangian multipliers with the transmission line constraints and associated power conservation (λ_1 and λ_2) and the Lagrangian multiplier associated with energy constraint (μ_1).

Hence for a 2 bus – 2 time period system (2b2tp) which results in a single transmission line with a given single energy constraint we have a total of 3 multipliers. Before exploring the formulation any further with the Lagrangian technique, we examine some fundamentals presented in the Lagrangian relaxation method in an attempt to shed brighter light on the formulation. Consider the method of Lagrangian relaxation:

Minimize: $F = f_1(x_1) + f_2(x_2)$

Subject to: $\bar{x} \in X$

$g(x_1) \geq 0$ and $g(x_2) \geq 0$ with $g(x_1, x_2) = g_1(x_1) + g_2(x_2)$ [34]

The Lagrangian,

$L(x_1, x_2, \lambda) = f_1(x_1) + f_2(x_2) + \lambda g(x_1, x_2)$ where λ is the Lagrange multiplier (dual variable). The Lagrangian dual function is defined as

$h(\lambda) = \min L(x, \lambda)$, which is called the Lagrangian sub-problem. The dual function is obtained by minimizing the Lagrangian function subject to the constraints $\bar{x} \in X$. The Lagrangian dual problem [D] of the problem [P] is formulated as:

[D] maximize $h(\lambda)$ with $\lambda \geq 0$ (note if a relaxed constraint is a "$\leq$" (less than or equal to) constraint, then the Lagrangian multiplier λ is ≤ 0 and equality constraints have an unrestricted multiplier.

Where $h(\lambda) = \min(f(x_1) + f(x_2) + \lambda g(x_1, x_2))$

Utilizing the Duality theorem:

1. Weak Duality Theorem: Suppose that $\bar{x}^* (x_1^*, x_2^*)$ is an optimal solution to the problem [P]. For any $\bar{\lambda} \geq 0$ ($\lambda_1 \geq 0$ and $\lambda_2 \geq 0$), we have $h(\bar{\lambda}) \leq f\left(\bar{x}^*\right)$.

   Where $f\left(\bar{x}^*\right)$ is the optimal objective value of [P].

This theorem shows that for a value of the Lagrangian multiplier, $\lambda \geq 0$, the value of the dual function provides a lower bound on the optimal objective function value of the original problem [P]. To obtain the best or largest lower bound for all possible λ , we need to solve the dual problem.

$$\max h(\lambda) = \max(\min(f(x_1) + f(x_2) + \lambda g(x_1, x_2))) \text{ with } \bar{\lambda} \geq 0$$

2. The dual function $h(\lambda)$ is a concave function.

The solution of the dual problem reduces to the search for the maximum of a concave function over the convex set $\bar{\lambda} \geq 0$. Moreover, we have established valid bounds for comparing objective function values of the Lagrangian dual problem [D] and the primal problem [P]. The relation between these can be written as:

$h(\bar{\lambda}) \le h(\bar{\lambda}^*) \le f(\bar{x}^*) \le f(\bar{x})$ where $\bar{\lambda}$ and $\bar{x}$ are the feasible solutions to the dual and primal problems respectively.

We now want to maximize $h(\lambda)$ with respect to λ

$\max h(\lambda) = \max(\min(f(x_1) + f(x_2) + \lambda g(x_1, x_2)))$

In pursuit of the maximization of $h(\lambda)$ we turn to establishing x_1 and x_2 in terms of λ, substitute and solve the dual function. Partial Derivatives of primal [P]:

$$\frac{\partial L(x_1, x_2, \lambda_1, \lambda_2)}{\partial x_1} = \frac{\partial f(x_1)}{\partial x_1} + \lambda_1 \frac{\partial g(x_1)}{\partial x_1} = 0 \text{ establishes } x_1 \text{ as function of } \lambda$$

$$\frac{\partial L(x_1, x_2, \lambda_1, \lambda_2)}{\partial x_2} = \frac{\partial f(x_2)}{\partial x_2} + \lambda_1 \frac{\partial g(x_2)}{\partial x_2} = 0 \text{ establishes } x_2 \text{ as function of } \lambda$$

$$\frac{\partial L(x_1, x_2, \lambda_1, \lambda_2)}{\partial \lambda_1} = g(x_1, x_2) = g_1(x_1) + g_2(x_2) \ge 0$$

Substituting we have $h(\lambda)$, which can produce an optimal λ.

Before examining the formulation relaxation, where constraints are relaxed and the sub-problems are formed it is important to recognize some properties of the Lagrangian multipliers in this formulation.

For example the gradient of L with respect to each variable equal to zero we see:

$$\frac{\partial L}{\partial P^1 g_1} = \frac{\partial G^1_{CP_1}}{\partial P^1 g_1} + \lambda_1 = 0 \qquad \frac{\partial L}{\partial P^1 g_2} = \frac{\partial G^1_{CP_2}}{\partial P^1 g_2} + \lambda_1 = 0$$

$$\frac{\partial L}{\partial P^2 g_1} = \frac{\partial G^2_{CP_1}}{\partial P^2 g_1} + \lambda_2 = 0 \qquad \frac{\partial L}{\partial P^1 d_1} = \frac{\partial D^1_{CP_1}}{\partial P^1 d_1} - \lambda_1 + \mu_1 = 0$$

$$\frac{\partial L}{\partial P^2 g_2} = \frac{\partial G^2_{CP_2}}{\partial P^2 g_2} + \lambda_2 = 0 \qquad \frac{\partial L}{\partial P^2 d_1} = \frac{\partial D^2_{CP_1}}{\partial P^2 d_1} - \lambda_2 + \mu_1 = 0$$

And....

$$\frac{\partial L}{\partial \lambda_1} = (t^1{}_{12} + t^1{}_{21}) = 0 \qquad \frac{\partial L}{\partial \mu_1} = (Pd_1^1 + Pd_1^2 - E_1) = 0$$

$$\frac{\partial L}{\partial \lambda_2} = (t^2{}_{12} + t^2{}_{21}) = 0$$

Examining the formulations above presents interesting physical interpretations that need to be considered in the further investigation of Lagrangian relaxation.

1. Energy constraints at a bus are directly related to the Lagrangians μ_i and the transmission lines between buses are directly related to the Lagrangians λ_j
2. The partial derivatives of L with respect to the Lagrangian multipliers return the original constraints of the system.
3. $(t^1{}_{12} + t^1{}_{21}) = Pg_1^1 - Pd_1^1 + Pg_2^1 - Pd_2^1 = 0$: represents the sum of all generation must be equal to the sum of all demand, which is exactly what we expect to see in the instantaneous case. In a side discussion later we will examine an approach where all the constraints can be examined as a single constraint,

which is a sum of all constraints. This establishes a single Lagrangian multiplier changing the structure of the Lagrangian (L) slightly.

4. The energy Lagrangian multiplier μ_1 relates the transmission line Lagrangian multipliers.

Now applying this methodology of Lagrangian relaxation to the 2b2tp we begin by relaxing the constraints for the bus given by the transmission line constraint and the time period given by the energy constraint. The resulting sub-problem formed is now a simpler local problem at each bus for each time period. Hence for a given bus (i), time period (j):

Bus_i and TP_j →sbpr ij: minimize $G^j_{CP_i} + D^j_{CP_i} + \lambda^j_p (Pg^j_i - Pd^j_i) + \mu_i (Pd^j_i)$ for the given values of the associated Lagrangians. Hence, in the 2b2tp systems the resulting sub-problems:

sbpr 11: minimize $G^1_{CP_1} + D^1_{CP_1} + \lambda^1_1 (Pg^1_1 - Pd^1_1) + \mu_1 (Pd^1_1)$

sbpr 21: minimize $G^1_{CP_2} + D^1_{CP_2} + \lambda^1_1 (Pg^1_2 - Pd^1_2)$

sbpr 12: minimize $G^2_{CP_1} + D^2_{CP_1} + \lambda^2_1 (Pg^2_1 - Pd^2_1) + \mu_1 (Pd^2_1)$

sbpr 22: minimize $G^2_{CP_2} + D^2_{CP_2} + \lambda^2_1 (Pg^2_2 - Pd^2_2)$

The actual formulation of relaxing a constraint is not easily understood when there are numerous variables and constraints, hence a simpler model can provide insight to the approach of relaxation and merits a short discussion. To demonstrate the method of relaxation, we set up an optimization problem: minimize $x^3 + y^2$

Subject to: $x + y = 9$, $x \geq 0$, $y \geq 0$

As a first approach we will consider a classical approach;

1. Using the constraint solve for y in terms of x: $y = 9 - x$
2. Substitute (1) into the objective function and examine the first and second derivatives for insight to minimums and maximums: $obj = x^3 + (9-x)^2$
   a. 1st derivative: $3x^2 + 2x - 18$ with zeros at x = -2.8054 and x = 2.1387, which represents a minimum or a maximum.
   b. 2nd derivative $6x + 2$, where the 2nd derivative is positive for $x > -\frac{1}{3}$, thus the function is concave up for $x > -\frac{1}{3}$ resulting in x=2.1387 being a minimum and the only viable solution.
3. The results are x = 2.1387 and y = 6.86.13 with the objective = 56.8394.

The next approach is to demonstrate the relaxation method. In this case the Lagrangian becomes: $L = x^3 + y^2 + \lambda(x + y - 9)$ and via the Weak Duality Theorem the Lagrangian sub-problem is $h(\lambda) = \min(L(x, y, \lambda) = \min[x^3 + y^2 + \lambda(x + y - 9)]$. Using the Duality Theorems to find λ so that the largest lower bound is obtained by maximizing $h(\lambda)$ over λ, which implies: $\max_\lambda(h(\lambda))$. However we take this a step further and relax the constraint: $x + y = 9$, and we relax the constraint so that y and x are not dependent, thus the sub-problems produced from the Lagrangian are:

1. Minimize $x^3 + \lambda x$
2. Minimize $y^2 + \lambda y$

The value of λ is generally set to zero and the minimum value of each sub-problem is searched for via all potential values of x and y. For each of these sub-problems, we know that $0 \le x \le 9$ and $0 \le y \le 9$. Hence we evaluate each sub-problem over discretized vector from 0 to 9 and determine the minimum value for λ. The minimum value of each sub-problem is represented by a feasible solution x and feasible solution y. The feasible solutions are then evaluated against the constraint to determine how close it is to zero. The constraint is $ct = x + y - 9$. The corresponding value of the constraint (ct) then drives the search for the appropriate Lagrangian, λ. Below are result of a MATLAB algorithm designed to solve the problem while implementing the Lagrangian relaxation. In this algorithm, x and y were discretized into steps of .001 and a minimum constraint error was set to .01. The algorithm ran a total of 16 times and produced the following:

$x = 2.1380$

$y = 6.8850$

$\lambda = -13.7109$

And producing in a minimum to the objective function of 56.7639, which is in line with the exact solution via derivatives and solutions to polynomials. If we continue to adjust the step sizes, search approach to the Lagrangian, and constraint values we can increase accuracy and speed of the algorithm. Figure 11 is a graph of the x solution, y solution, and Figure 12 is the Lagrangian at each iteration of the algorithm.

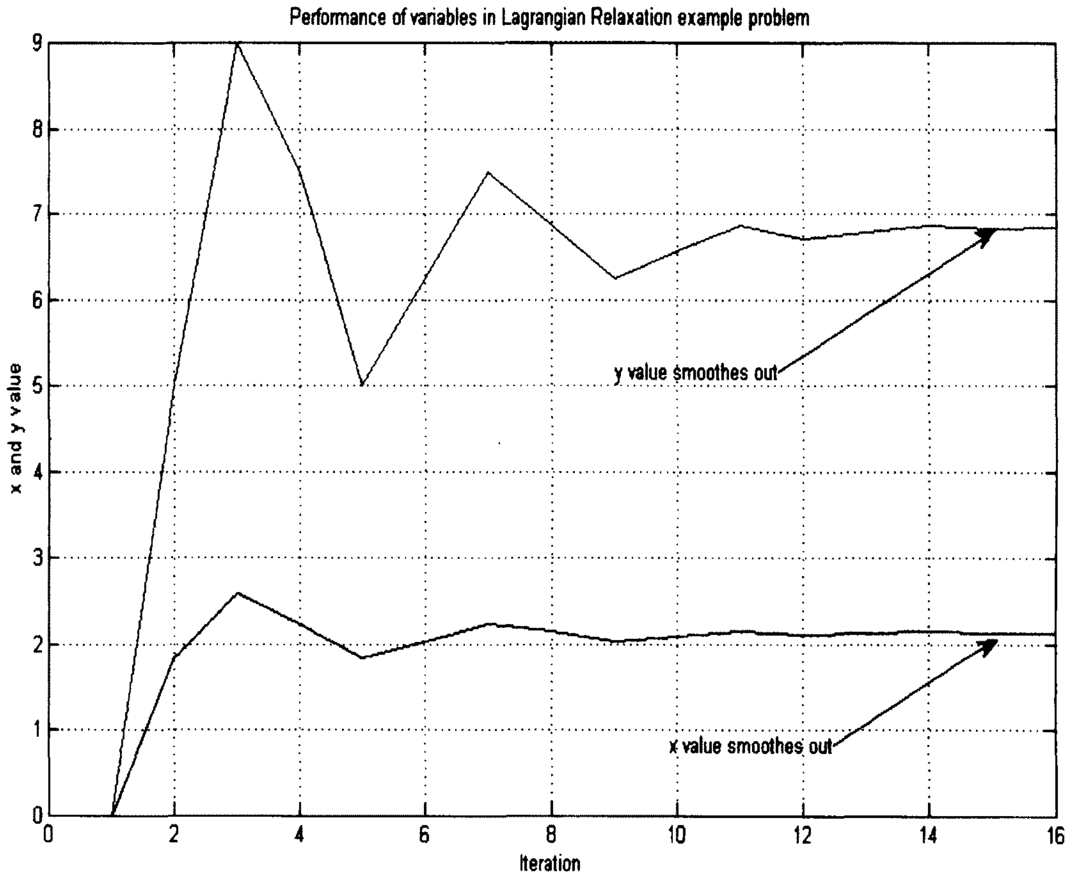

Figure 11: Performance of X and Y in Lagrangian Relaxation Example

Effectively the relaxation of the constraint has provided a set of sub-problems that can be solved independently by varying the Lagrangian. Varying of Lagrangian within Lagrangian Relaxation provides a unique approach and insight to solving global objective functions.

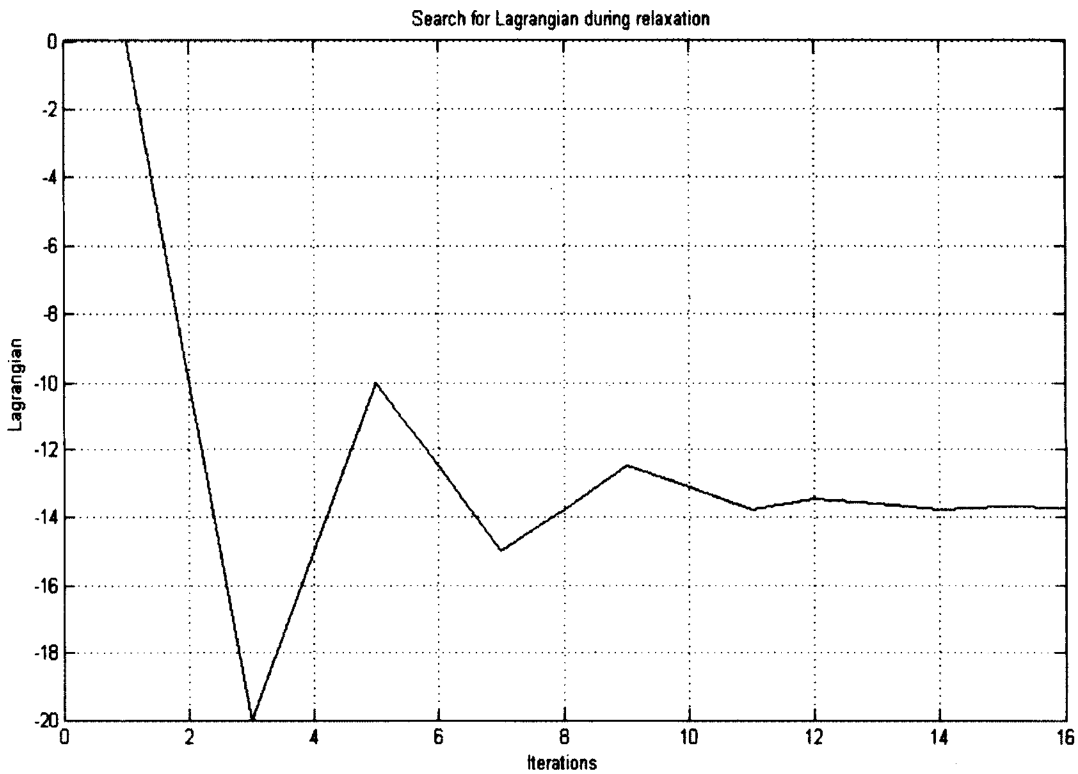

Figure 12: Lagrangian Value in the Lagrangian Relaxation Example

. Ultimately we see that the Lagrangian provides information on the system, which we introduce later in the microgrid model. Below is a table presenting the variables, Lagrangian, constraint, objective, and step size of the Lagrangian for each iteration or the algorithm (Table 1).

In Table 1, the value of the Lagrangian, λ, represents a search from the initial value of zero in an initial step size of 10. As the algorithm evaluates the constraint (ct) it adjusts its step size and direction.

Table 1: Algorithm variables form Lagrangian Relaxation example

Iteration	X	Y	λ	Constraint	Objective	Stepsize
1	0	0	0	-9	0	10
2	1.826	5	-10	-2.174	31.08838798	10
3	2.582	9	-20	2.582	98.21348137	10
4	2.236	7.5	-15	0.736	67.42932026	5
5	1.826	5	-10	-2.174	31.08838798	5
6	2.041	6.25	-12.5	-0.709	47.56465492	2.5
7	2.236	7.5	-15	0.736	67.42932026	2.5
8	2.141	6.875	-13.75	0.016	57.07971422	1.25
9	2.041	6.25	-12.5	-0.709	47.56465492	1.25
10	2.092	6.562	-13.125	-0.346	52.21540669	0.625
11	2.141	6.875	-13.75	0.016	57.07971422	0.625
12	2.116	6.719	-13.4375	-0.165	54.6192579	0.3125
13	2.129	6.797	-13.59375	-0.074	55.84920169	0.15625
14	2.141	6.875	-13.75	0.016	57.07971422	0.15625
15	2.135	6.836	-13.671875	-0.029	56.46270638	0.078125
16	2.138	6.855	-13.7109375	-0.007	56.76391707	0.0390625

To validate the minimum we can allow x and y to vary slightly we can see that we are at a minimum for the solution and still within the constraint (Table 2).

Refocusing to the microgrid formulation and the 2b2tp system at hand, the ability to relax constraints on the global optimization problems creates a significant

Table 2: Validation of minimum

delta	new x	new y	Constraint	Objective
-0.5	1.6387	7.3613	0	58.5892
-0.4	1.7387	7.2613	0	57.9827
-0.3	1.8387	7.1613	0	57.50053
-0.2	1.9387	7.0613	0	57.14867
-0.1	2.0387	6.9613	0	56.93314
0	2.1387	6.8613	0	56.85993
0.1	2.2387	6.7613	0	56.93504
0.2	2.3387	6.6613	0	57.16448
0.3	2.4387	6.5613	0	57.55424
0.4	2.5387	6.4613	0	58.11031
0.5	2.6387	6.3613	0	58.83871

opportunity to formulate sub-problems at each bus and each time frame. This aspect of the relaxation is important as it begins to de-couple the interactions of all buses and time frames as represented in the original global objective. This de-coupling of the system into sub-problems allows the architecture to support an agent, present at each bus or point of common coupling, to determine its participation into the systems, i.e. generation or demand into the system.

The sub-problem is completely decoupled from the system, but is integrated between neighbors via the communicated Lagrangians associated with the transmission lines. What ultimately must be determined is the communication of associated Lagrangians. In the example problem ($x^3 + y^2$), there was a single Lagrangian; as the formulation shifts to the microgrid model, the Lagrangians are associated with each interconnection between buses or transmission lines for each time period as well as being associated with each energy constraint for each bus. Hence the number of Lagrangians associated with microgrid problem increases quickly with transmission lines and energy constraints. However the sub-problems reduces the complexity to a single bus and time period allowing for Lagrangians associated with that bus and time period. As presented earlier in the 2b2tp problem, the sub-problem 11: $G_{CP_1}^1 + D_{CP_1}^1 + \lambda_1^1(Pg_1^1 - Pd_1^1) + \mu_1(Pd_1^1)$. There are 2 associated Lagrangians in the problem; λ_1^1 associated with time period one and transmission line 1 as well as μ_1 associated with the energy constraint for Pd_1^1 and Pd_1^2. Establishing the Lagrangian Relaxation method in the microgrid formulation has the same high level characteristics as the example problem, however wth the expansion of different topologies, increased preference functions for demand and generation, as well as increasing the constraints, complicates the formulation. Thus in the next sections we will continue the 2b2tp model and step through some of the intricacies and then expand the models further identifying differences and important factors.

In calculating the sub-problems,

sbpr 11: minimize $G_{CP_1}^1 + D_{CP_1}^1 + \lambda_1^1(Pg_1^1 - Pd_1^1) + \mu_1(Pd_1^1)$

sbpr 21: minimize $G_{CP_2}^1 + D_{CP_2}^1 + \lambda_1^1(Pg_2^1 - Pd_2^1)$

sbpr 12: minimize $G_{CP_1}^2 + D_{CP_1}^2 + \lambda_1^2(Pg_1^2 - Pd_1^2) + \mu_1(Pd_1^2)$

sbpr 22: minimize $G_{CP_2}^2 + D_{CP_2}^2 + \lambda_1^2(Pg_2^2 - Pd_2^2)$

a value is chosen for each of the three different Lagrangian multipliers and a minimum is determined for each sub-problem based upon the Lagrangian multipliers and values of demand and generation based upon each corresponding preference function. The determination of a minimum is accomplished by a brute force approach by comparing each discretized values of both the generation against each discretized value of the demand preference functions. At the determined minimum the associated input values for the preference functions correspond to values of generation and demand ($P^n_{g_m}$ and $P^n_{d_m}$). The values for generation and demand, $P^n_{g_m}$ and $P^n_{d_m}$, are then examined in the transmission line and energy constraints for every bus and every time period. It is important to note that the transmission line constraints satisfy the power flow in a single time period and the energy constraints are over all time periods considered. The results of the evaluation of constraint then guide the adjustment of the Lagrangians.

To illustrate the implementation of Lagrangian relaxation in the optimization, a specific example is introduced following the 2b2tp problem being presented. To accomplish the example, the systems configuration is defined in four Excel spreadsheet:

1. Topology.xlsx
2. GenerationPreference.xlsx
3. Demand.xlsx
4. SeriesImpedance.xlsx

These four spreadsheets provide flexibility via configuration parameters to adjust to several different factors of the system. Overall there are several high level concepts necessary to run a successful configuration. The high level concepts include:

1. Topology of the microgrid
2. Electrical parameters (Line impedance) of the interconnecting transmission / distribution system
3. Identifying bus characteristics of demand and generation, typically provided by preference functions, fixed demand, fixed generation, and/or energy constraints.
4. Characterization of generation and demand preference function.

In the current 2b2tp configuration generation and demand preference functions are associated for each bus. The generation and demand capacities are set to 10kW and are discretized in 0.1kW steps. Bus 1 has an energy constraint of $E_1 = 10kWh$ over both time periods and bus 2 has a fixed demand of 3 kW during time period 1 and 5kW during time period 2. Without diving into a detailed physical significance of the preference function, a set of simple polynomial function that are derived from data sets have been chosen for this. The generation and demand preference functions are graphed below in Figure 13. The demand function could be a representation of a willingness to pay more for a critical load, then less for deferrable, and finally the smallest amount for discretionary demand. The generation functions represent the increased cost of fuel and maintenance of a generator as output is increased. There is a more detailed discussion on preference functions in later sections. Results from this configuration are in Table 3 show the higher cost of bus 1 generator preference and as well as higher preference in its demand curve as depicted in figure 13. Meaning we see a larger generation contribution for the system coming from the less expensive generator at bus 2 and a higher demand cost at bus 1.

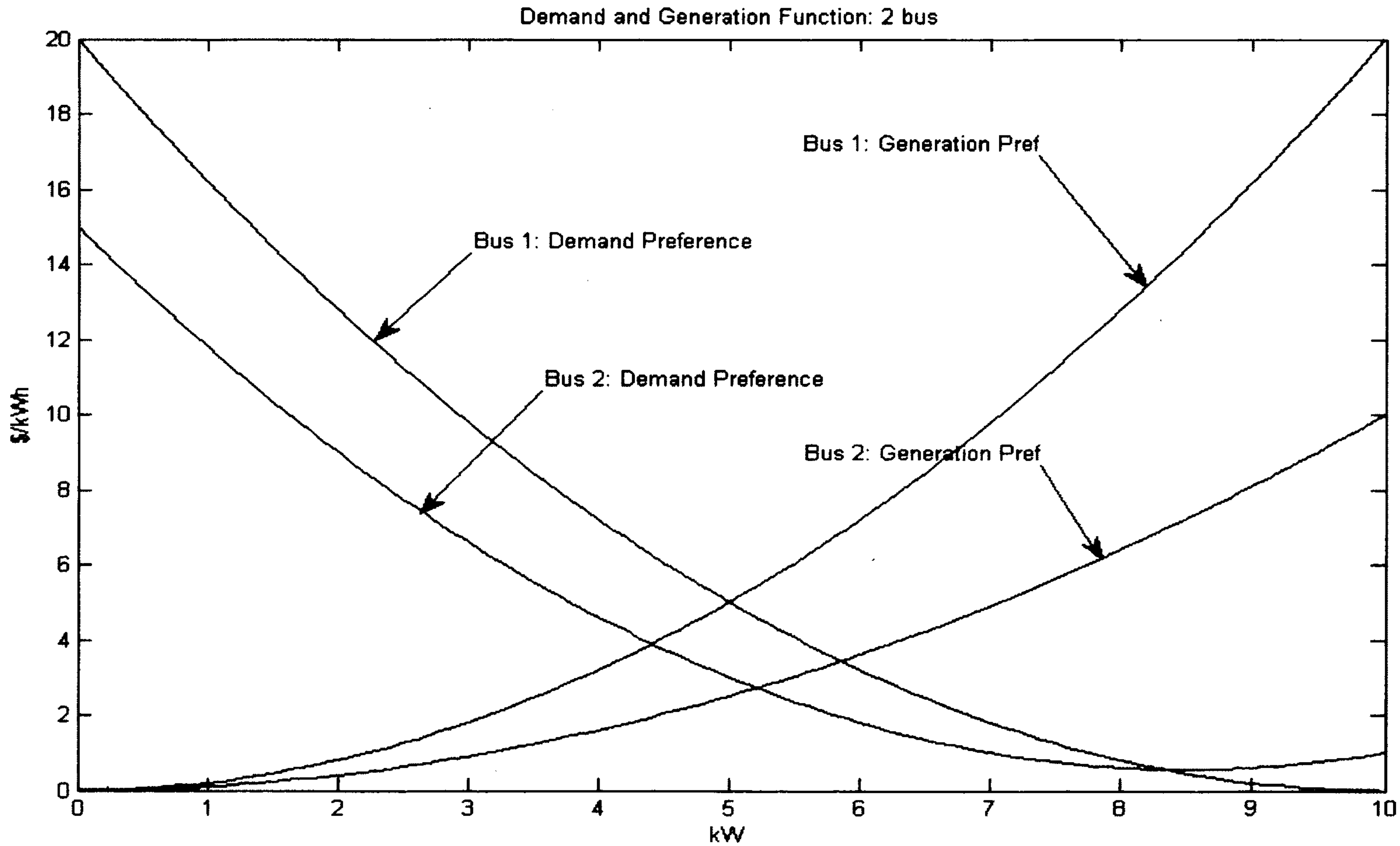

Figure 13: 2b2Tp Generation and Demand Preferences

Table 3: 2b2tp v1

subproblem	sbmin	Pg	Pd	gCost	dCost	λ	μ
sb11	12.773	2.8	5.3	1.568	4.418	-1.125	0.75
sb21	13.155	3.3	4.8	2.178	5.408	-1.313	0.75
sb12	6.811	5.6	3	3.136	6.6	-1.125	0
sb22	5.256	6.6	5	4.356	3	-1.313	0

Constraints	
Line 1 - TP1	0.1
Line 1 - TP2	0.1
Energy1	0.1

Total Minimum of Objective function	30.644

We see that all constraints have been met within the specified tolerances in the configuration (<3% of bus capacity) and if the tolerances are tightened up we get more refined results in Table 4. Note the constraint results are smaller than Table 3. In the more constrained example, Table 4, the algorithm had a total of 43 iterations, while the less constrained case, Table 3, has 29 iterations. Remember that during a single iteration every value of generation and demand are evaluated at every bus and every time period, hence a significant increase in the amount of comparisons in the algorithm. The microgrid problem has the same characteristics of searching for the appropriate Lagrangian to meet the constraints as the example problem demonstrated. However in the microgrid case, Lagrangians have been identified for each transmission line and time period as well as for each energy constraint. Thus the search happens in each time period to solve the transmission line constraints and then the values are compared to the energy constraint and then the energy Lagrangians are adjusted and the process starts over again in search for transmission line Lagrangians. This process is more difficult to see graphically as the transmission line Lagrangians settle for that particular time period. Below $Pg_1^1, Pd_1^1, \lambda_1^1, \mu_1$ are represented

Table 4: 2b2tp v2

subproblem	sbmin	Pg	Pd	gCost	dCost	λ	μ
sb11	12.976	2.7	5.3	1.458	4.418	-1.1	0.8
sb21	13.376	3.2	4.7	2.048	5.618	-1.3	0.8
sb12	6.875	5.5	3	3.025	6.6	-1.1	0
sb22	5.275	6.5	5	4.225	3	-1.3	0

Constraints	
Line 1 - TP1	-0.1
Line 1 - TP2	0
Energy1	0

Total Minimum of Objective function	30.392

The variable "m", in Figure 14, represents the iterations of the energy Lagrangian. During each iteration of the energy Lagrangian, system minimums were found that have met the transmission line constraints, but did not meet the energy constraints. Hence the Lagrangian multiplier associated with the energy constraint (μ) was adjusted and the search for a system minimum began again. The sixth iteration of the energy Lagrangian, as seen in Figure 14, provided a system minimum with both energy and transmission line constraints met.

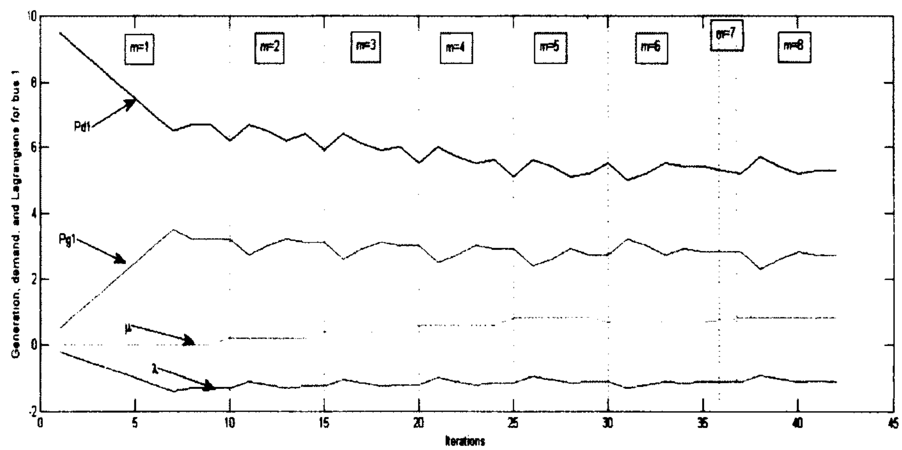

Figure 14: 2b2tp Results Showing Convergence

The next step is to examine the results of the same problem but adjusting the demand slightly. Previously bus 2 has a fixed demand. In the following case we will use a 2 bus system with demand preferences only and finally with demand preferences and energy constraints.

Case 1: Demand preferences only, no Energy constraints

This is a simpler case and each time frame is identical to the other due to the fact that the generator and demand preferences do not change from time period to time period. As seen below, the results from time period 1 and time period 2 are identical. Note that the generator at bus 2 has a preference/cost curve that has less preference/cost than bus 1; hence bus 2 has a higher output (Table 5). This is directly correlated by the global optimization problem of minimizing cost while meeting power constraints.

Table 5: 2b2Tp case 1

subproblem	sbmin	Pg	Pd	gCost	dCost	λ	μ
sb11	9.311	3.7	6.3	2.738	2.738	-1.475	0
sb21	9.311	3.7	6.3	2.738	2.738	-1.475	0
sb12	4.929	7.4	4.8	5.476	3.288	-1.475	0
sb22	4.929	7.4	4.8	5.476	3.288	-1.475	0

Constraints	
Line 1 - TP1	0
Line 1 - TP2	0
Energy1	N/A

Total Minimum of Objective function	28.48

Case 2: Demand preferences only, 1 Energy constraint bus 1($E_1 = 16$)

The energy constraint at bus 1 is set to 16 (kWh) for over both time periods. Thus we should expect to see the sum of the demand for bus 1 over both time periods be equivalent to 16. Additionally since the demand and generation preferences are not changing over the time period, we should expect to see a higher demand at bus 1 than the previous example, hence given the demand preference at bus 2, the demand serviced will be reduced (Table 6).

Case 3: Demand preferences only, Energy constraints ($E_1 = 16, E_2 = 14$)

The energy constraints now become the dominant factor as both bus 1 and bus2 must meet the energy constraint. It should be noted that the generator at bus 2 is producing its maximum amount as expected due to the cost differences between generator 1 and generator 2 (Table 7).

Table 6: 2b2Tp case 2

subproblem	sbmin	Pg	Pd	gCost	dCost	λ	μ
sb11	3.797	4.1	8	3.362	0.8	-1.65	-0.85
sb21	3.797	4.1	8	3.362	0.8	-1.65	-0.85
sb12	4.366	8.3	4.4	6.889	3.912	-1.65	0
sb22	4.366	8.3	4.4	6.889	3.912	-1.65	0

Constraints	
Line 1 - TP1	0
Line 1 - TP2	0
Energy1	0

Total Minimum of Objective function	29.926

The results from the 4 different demand configurations illustrate demand and generation preferences not changing over the time periods.

Table 7: 2b2Tp case 3

subproblem	sbmin	Pg	Pd	gCost	dCost	λ	μ
sb11	2.399	5	7.9	5	0.882	-2	-1.175
sb21	2.399	5	7.9	5	0.882	-2	-1.175
sb12	-4.8	10	7	10	1	-2	-1.4
sb22	-4.8	10	7	10	1	-2	-1.4

Constraints	
Line 1 - TP1	0.1
Line 1 - TP2	0.1
Energy1	-0.2

Total Minimum of Objective function	33.764

It is the constant value for the transmission line Lagrangian multiplier, λ, that shows this. If the preference functions did change from time period to time period, generally the Lagrangian multiplier for the transmission line would also change .

Now that the Lagrangian relaxation algorithm has been introduced with the microgrid characters and descriptions, we expand the discussion to systems with 3 or more buses which drives the number of transmission lines and associated Lagrangians multipliers.

As the number of buses increase there are subtle changes in both the sub-problem and constraints that need to be addresses. The new Lagrangians expands with additional generation and demand preferences as well as Lagrangian multipliers for each transmission line. If we ignore the energy constraints for the time being and only consider one time period we have: $L = M + \lambda_1(t_{12} + t_{21}) + \lambda_2(t_{23} + t_{32})$ for a three bus system. This system is shown in Figure 15 with the Lagrangian multipliers associated with transmission lines:

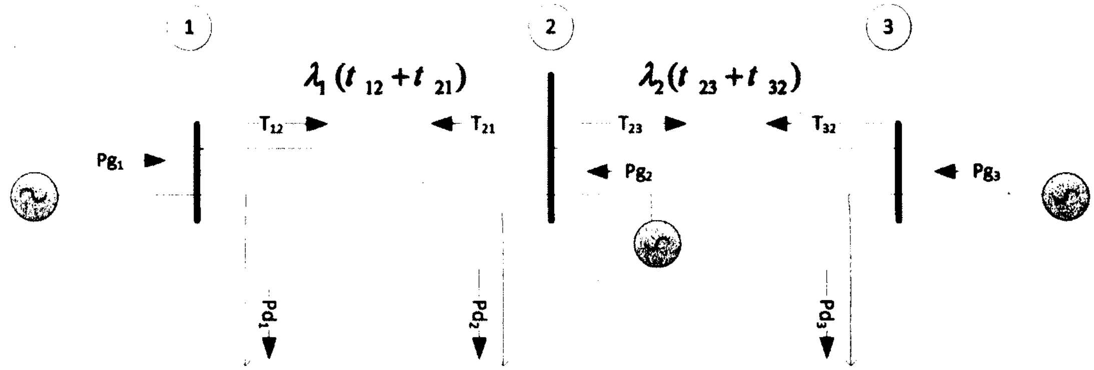

Figure 15: 3 Bus Topology

It is easy to see as transmission lines are added to the system, additional Lagrangian multipliers are brought into the overall Lagrangian. Before we begin to relax the constraints and form the sub-problem it is important to examine one property of the transmission line constraints. The transmission line constraint in this global problem is simply a representation of the physical power flow, where power entering the transmission line must leave the power line represented by $t_{ij}+t_{ji}=0$. For a bus with a single transmission we find t_{ij} by examining bus_i. For this example at bus 1 we see $Pg_1 - Pd_1 - t_{12} = 0$ or $t_{12} = Pg_1 - Pd_1$, and similarly at bus 3 we see a similar situation, $Pg_3 - Pd_3 - t_{32} = 0$ or $t_{32} = Pg_3 - Pd_3$. For buses with one transmission line the sub-problems are simply a function of generation and demand at each bus. However at bus 2, the bus with more than one transmission line, the constraint is subtly different, $Pg_2 - Pd_2 - t_{21} - t_{23} = 0$. The addition of the power outgoing or incoming on all the transmission lines for a multi-transmission line bus introduces an important concept in this application. If we examine the sub-problem at bus 2 at time period k, we see: sbpr(2k) minimize $G^k_{CP_2} + D^k_{CP_2} + \lambda^k_1(t^k_{21}) + \lambda^k_2(t^k_{23}) + \mu_2(Pd^k_2)$. Determining the value of t_{21} and t_{23} for the sub-problem is not as apparent as the single transmission line bus. We cannot simply substitute the value of $Pg_2 - Pd_2$ in for t_{21} or t_{23}, as t_{21} is dependent up $Pg_2 - Pd_2$ and t_{23}, similarly, t_{23} is dependent up $Pg_2 - Pd_2$ and t_{21}. The physical interpretation of this problem could be presented as the bus participating in a larger system, where power is entering and exiting the bus for other parts of the network, hence the bus must have some information about the downstream and upstream buses and its activities. This is represents an important factor any implementation of this algorithm. Agents residing on the bus must communicate to their downstream and upstream counterparts on the buses transmission lines. The implementation of this 'dc-power flow' is required to estimate the constraint for any bus that has more than one transmission line.

In this algorithm a technique from a dc load flow is implemented to estimate power in and out of the bus from multiple transmission lines. For a single transmission line bus_i we introduce ∂_i, where $Pg_i - Pd_i = \frac{\partial_i - \partial_j}{X_{ij}}$. This equation is similar to the power flow formulation and Ohm's Law, where $V_{ij} = Z_{ij} I_{ij}$. In the algorithm we define ∂_i for a single bus system as $\partial_i = X_{ij}(Pg_i - Pd_i) + \partial_j$, where ∂_j is communicated from bus_j and X_{ij} is the impedance of the transmission line. In the algorithm the $\partial's$ are initially set to zero and as each bus is addressed in the sub-problems a value for ∂ is calculated and tracked. Hence for a bus_i connected bus_k, bus_l, and bus_m, the problem expands to $\partial_i = \frac{[(Pg_i - Pd_i) + \frac{\partial_k}{X_{ik}} + \frac{\partial_l}{X_{il}} + \frac{\partial_m}{X_{im}}]}{\frac{1}{X_{ik}} + \frac{1}{X_{il}} + \frac{1}{X_{im}}}$.

This technique in the algorithm based upon communicating ∂_i for each bus attached and provides an estimate of power flow in and out of transmission lines attached to the bus. (Note: this method of could be extended to include both voltage and reactive power.)

In addition to the subtle changes in the sub-problem, another fact in the transmission line constraints need further examination. If you examine the 3 bus system and its associated 2 constraints, $t_{12} + t_{21} = 0$ and $t_{23} + t_{32} = 0$ there is an interesting property. We know that $t_{12} = Pg_1 - Pd_1$, $t_{32} = Pg_3 - Pd_3$, and $Pg_2 - Pd_2 = t_{21} + t_{23}$, and if we substitute into either constraint the result is: $Pg_1 - Pd_1 + Pg_2 - Pd_2 + Pg_3 + Pd_3 = 0$. Hence each transmission line constraint can be viewed as the same constraint for the entire system. This represents an interesting view when re-writing the original Lagrangian to the global optimization problem. This is discussed later as alternative perspective which provides some validation of the relaxation methodology.

INTERPRETATION OF THE LAGRANGIAN RELAXATION

So far the Lagrangian Relaxation method has been outline for solving a global minimization problem in application for a defined microgrid and associated actors. A simple system has been demonstrated and implementation via the algorithm presented. One of the important aspects of applying the Lagrangian Relaxation method is observing the physical implication of the algorithm. Previously we have mentioned the sub-problem in the algorithm represents a local problem that can potentially be solved by an agent present at a bus. Additionally we have examined the need to pass information between agents, such as $\partial's$ and the Lagrangian multipliers associated with the transmission line between two buses. Just as the sub-problem is local to the bus, the communication is local between associated buses with transmission lines interconnecting them. This has direct implication to requirements of a system which implements this type of algorithm. The solution of the algorithm represents local computation and local communications, different from a centralized computed solution with centralized communication as most power systems utilize today. One interpretation is to view an agent associated with a transmission line presenting a Lagrangian multiplier, λ_i (Lambda i), to each local bus agent. On receipt of the multiplier, the local agent on the bus will minimize its local sub-problem and find a value of generation and/or demand based upon its preferences. These values are communicated back to the transmission line agent which then compares the values against the transmission line constraint for any mismatch. If there is a mismatch the value of the transmission lines Lagrangian is adjusted based upon the mismatch and again presented to the bus agents. This continues until the mismatch is satisfied against the constraint. This type of interaction (a value of λ_t being communicated to buses at each end of the transmission line) can be easily seen in a 3 bus system (Figure 16), where generation is available at Bus2 and demand is required at Bus1 and Bus3.

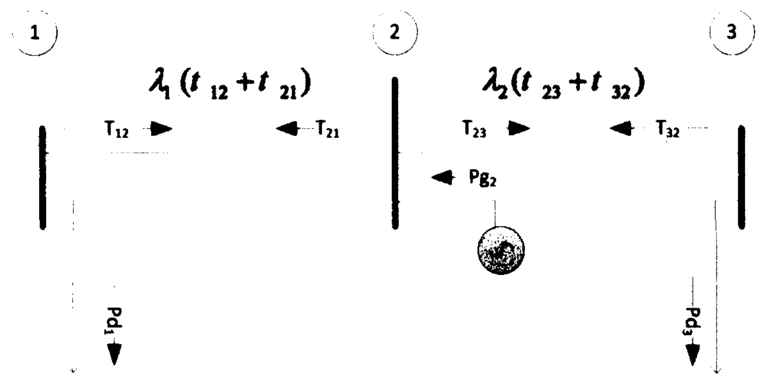

Figure 16: 3 Bus System

Figure 17 represents the value of Pd_1, Pd_3, Pg_2, and the Lagrangian multipliers λ_1 and λ_2. The first iteration represents the transmission line agent presenting a value of $\lambda = 0$ to both bus agents. At each bus the sub-problem is solved with the given Lagrangian multiplier. In this particular case, only Bus1 and Bus3 have demand and Bus2 has generation. The value of $\lambda = 0$ from the transmission line agent, elicits a value of demand ($Pd_1 = 10, Pd_3 = 8$, the maximum demand at the bus) based upon

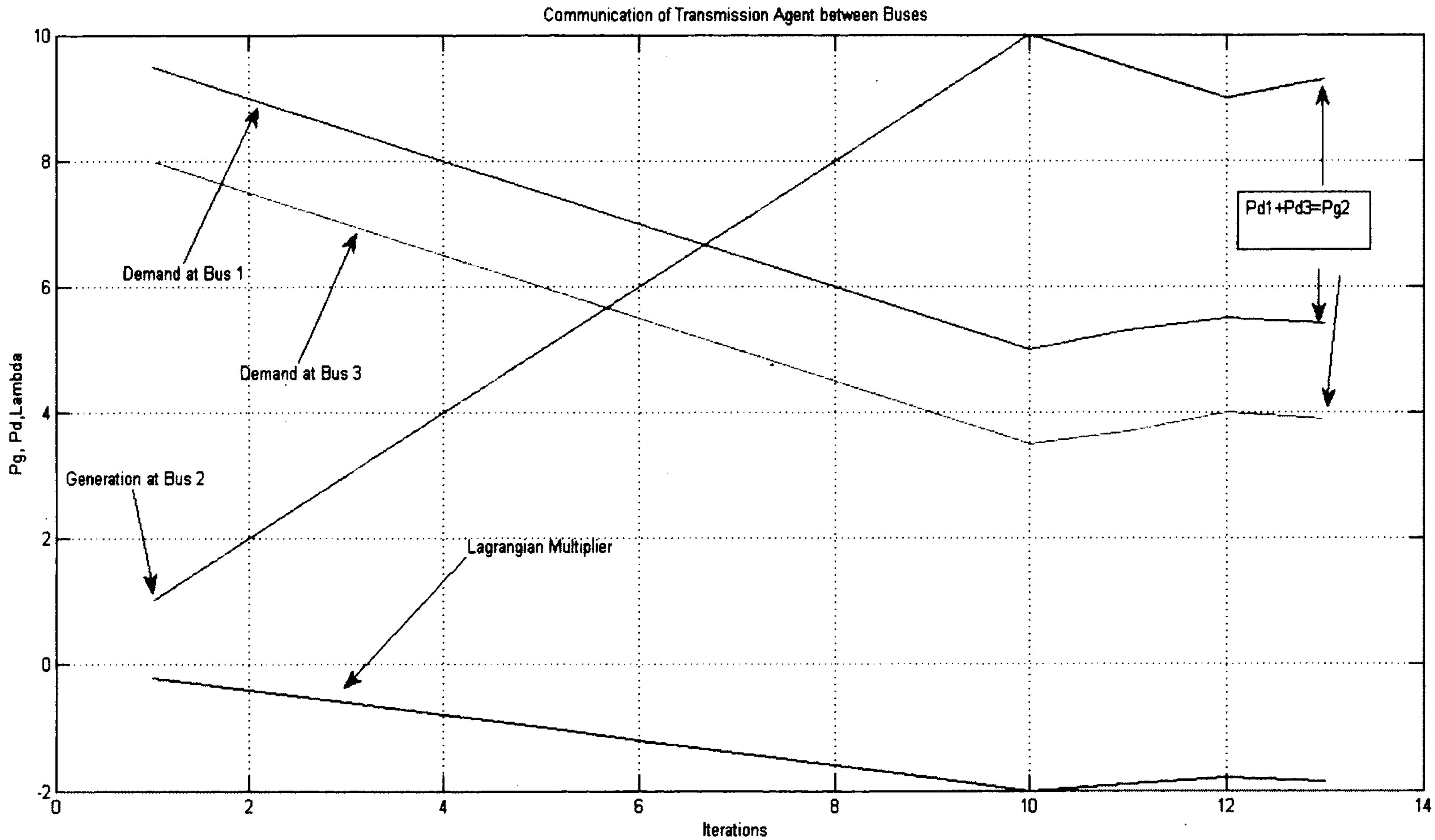

Figure 17: Communication of Lagrangian Multipliers

each demand preference function at bus1 and bus3, while bus2 produces a generation value ($Pg_2 = 0$, the minimum generation) based upon its generation preference function. It is important to recognize that demand is at a maximum and generation at a minimum. One can view, $\lambda = 0$ as a bid of energy cost in a pseudo market. In this pseudo market the generators are considered sellers and the loads buyers and the transmission line agents the auctioneers. . As the first iteration of a bid is submitted, $\lambda = 0$, the agent sees a mismatch of zero generation and demand at 14. The agent/auctioneer then begins to change the bid or Lagrangian multiplier based upon the mismatch. In this particular reference, the value of the Lagrangian multiplier will go in the direction of the mismatch. In other words, if the mismatch is negative the Lagrangian will be to a lower value, and similarly with a positive value, the multiplier will move up in value. As the Lagrangian is reduced in this case, each bus produces a value of demand and generation that is a local minimum and eventually the system physical constraints are met. This is understood better if you examine Figure 17 and notice the iteration steps on the horizontal axis. The values of demand are reduced and the generation is increasing, eventually becoming equal. It is important to note that the sign of the Lagrangian multiplier is easily adapted in the original formulation of the Lagrangian and can be positive or negative. As the iterations continue with the transmission line agent/auctioneer adjusts the bid (Lagrangian multiplier) and computes the mismatch between generation and demand until the constraints have been met. The values of the converged solution are:

$Pd_1 = 5.4$, $Pg_2 = 9.3$, $Pd_3 = 3.9$, $\lambda_1 = -1.85$, $\lambda_2 = -1.85$ which was found in13 iterations of the algorithm.

This case of 3 bus system presented demonstrates an interesting characteristic of the system where the Lagrangian multipliers are equal. This characteristic is related to the alternative approach previously mentioned. This approach examines the aspect of each transmission line constraint being equivalent to the sum of all demand and generation. This property can be illustrated clearly in the 3 bus configuration. The 3 bus configuration has 2 transmission lines constraints:

$$t_{12} + t_{21} = 0$$

$$t_{23} + t_{32} = 0$$

We know the sum of power into each bus:

$$Pg_1 - Pd_1 - t_{12} = 0 \Rightarrow t_{12} = Pg_1 - Pd_1$$

$$Pg_3 - Pd_3 - t_{32} = 0 \Rightarrow t_{32} = Pg_3 - Pd_3$$

$$Pg_2 - Pd_2 - t_{21} - t_{23} = 0$$

Substituting for t_{12} and t_{32} the resulting constraint is

$$(Pg_1 - Pd_1) + (Pg_2 - Pd_2) + (Pg_3 - Pd_3) = \sum_{i=1}^{n} Pg_i - \sum_{i=1}^{n} Pd_i \ .$$

This reduction of constraints represents two important concepts will be introduced in later discussion. The first concept is that every transmission line constraint is a combination of all the generation and demand. We will see this later as we move to reduce all Lagrangians in the system to a single Lagrangian.

$$t_{ij} + t_{ji} = \sum_{i=1}^{n} Pg_i - \sum_{i=1}^{n} Pd_i$$

The second concept is that t_{ij} represents all the generation and demand behind bus_i and similarly t_{ji} represents the generation and demand behind bus_j.

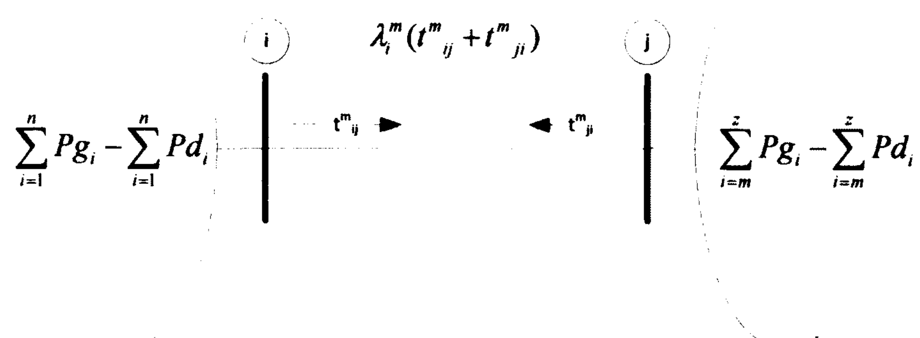

Figure 18: Properties of Transmission Line Constraints

The alternative approach reduces the number of constraints from one for each transmission line to a single constraint, which reduces the number of Lagrangian multipliers from the number of transmission lines to one. The underlying information is that the Lagrangian multipliers effectively become equal as seen in the example above. In fact with a single Lagrangian, the optimization can be solved with partial differential equation resulting in a convex function $h(\lambda)$ with a maximum at the value of λ where the constraint is met for the entire system.

The formulation using Lagrangian multipliers with a single constraint is presented below in with a 3b2tp example. In this example each bus has generation, demand preferences, and energy constraints which are specified in configuration spreadsheets. Below is the resulting dual function for values of λ over a specified region with the constraint value at the values determined for λ.

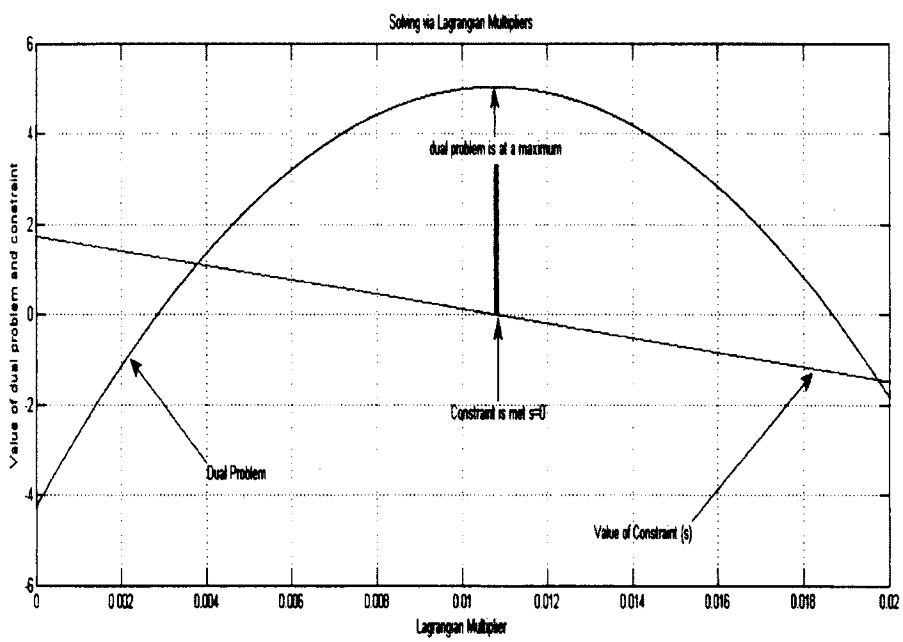

Figure 19: Convex dual function and constraint

Expanding the discussion on the Lagrangian multipliers being equivalent, it is possible to find solutions where the Lagrangian multipliers for the transmission lines are not equal, but the reason for this is related to quantizing the generation and demand preferences, topology, estimation on neighbor state, and errors in constraint determination. The best example to demonstrate this is to compare two systems, one with a radial configuration, Figure 20, and one with a star configuration, Figure 21.

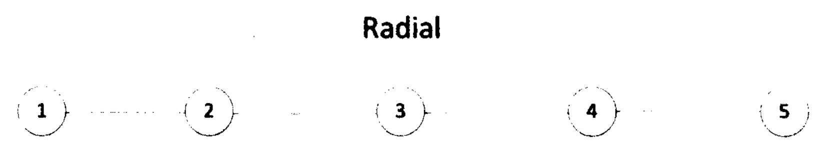

Figure 20: Radial Configuration

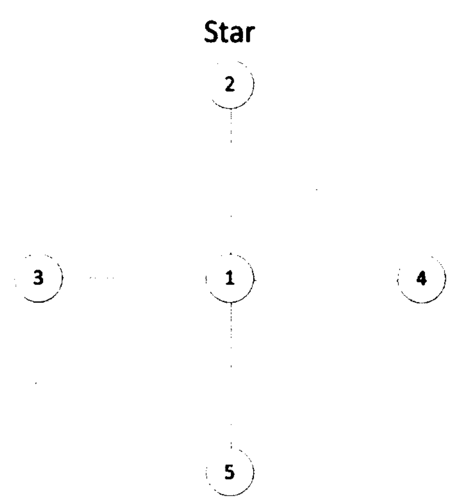

Figure 21: Star Configuration

For both examples, the same demand preference and generation preference configuration files are used; however the topology and series impedance configuration files are updated to reflect the physical interconnection differences. Hence each node requirements remain identical in each test. Each test was run with and without energy constraints (Table 8).

As the constraint limits are adjusted down or up we can see the radial configuration get closer to the star configuration. In this example, the determination of the system minimum is made by comparing a constraint limit value to the average of all constraints, hence the slightly different values along the radial configuration. Also in this example the transmission agents or auctioneers act independently when adjusting the bid.

Table 8: Transmission Line Lagrangian Multipliers

	Star Configuration w/o Energy Constraints				Radial Configuration w/o Energy Constraints			
	λ1	λ2	λ3	λ4	λ1	λ2	λ3	λ4
TP 1	-1.4	-1.4	-1.4	-1.4	-1.5	-1.2	-1.25	-1.25
TP 2	-1.4	-1.4	-1.4	-1.4	-1.5	-1.2	-1.25	-1.25

	Star Configuration w/ Energy Constraints				Radial Configuration w/ Energy Constraints			
	λ1	λ2	λ3	λ4	λ1	λ2	λ3	λ4
TP 1	-1.2	-1.2	-1.2	-1.2	-1.15	-1.7	-1.05	-1.05
TP 2	-1.2	-1.2	-1.2	-1.2	-1.15	-1.7	-1.05	-1.05

Table 9 demonstrates that the star configuration represents equal Lagrangian multipliers, and that the effects of estimating states via delta and errors due to constraint limits effect actual values in the radial configuration

Table 9: Adjusted constraint limits

	Star Configuration w/o Energy Constraints				Radial Configuration w/o Energy Constraints			
	λ1	λ2	λ3	λ4	λ1	λ2	λ3	λ4
TP 1	-1.35	-1.35	-1.35	-1.35	-1.55	-1.2375	-1.175	-1.175
TP 2	-1.35	-1.35	-1.35	-1.35	-1.55	-1.2375	-1.175	-1.175

In addition to understanding the significance of the Lagrangian multiplier associated with the transmission line, it is also important to examine the Lagrangian multiplier associated with the energy constraint. Unlike the transmission line Lagrangian multiplier, the energy constraint Lagrangian multiplier is solved locally at each bus between time periods. The energy constraint Lagrangians are independent of each other and remain unrelated based upon demand preference function and value of the energy constraint. Thus in an analogous picture, the local agent becomes the auctioneer for energy over all periods at the bus locally which directly effects the single time period demand and response to the transmission line agent/auctioneer. Further discussion on a market based upon this implementation is provided in the 'Examining Implementation' section.

THE CLASSICAL TEST CASE

The question of "what is λ?" needs to be addressed to relate the mathematical and engineering approach in establishing the algorithm and formulation. λ represents Lagrangian multiplier and via the partial derivatives are equal to the local gradients of the preference functions at the solution defined by the constraint. In other words, when the gradients are equal and the constraint is met. To best illustrate this we examine a simplified system with a 2bus1tp example with generation and a fixed demand. This problem is solved using three different methods to help relate the concepts. Using the global formulation presented:

Minimize the cost function: $f^T(P_{g_i}, P_{d_i}) = \sum_{i=1}^{m} G^T{}_{CP_i}(P_{g_i}) + \sum_{i=1}^{m} D^T{}_{CP_i}(P_{d_i})$

Subject to:
$$
\begin{aligned}
&P_{g_i} - P_{d_i} - t_{ij} = 0 \\
&t_{ij} + t_{ji} = 0 \\
&P_{g_i} \le P_{g_i\,\max} \\
&P_{d_i} \le P_{d_i\,\max}
\end{aligned}
$$

For the 2 bus example over a single time frame (m=2 and n=1):

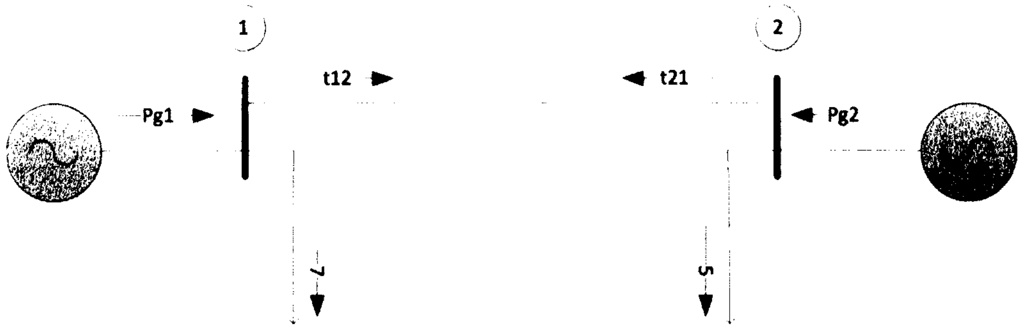

Figure 22: 2b1tp with Fixed Demand

Minimize $G^1_{cp_1}(Pg_1)+G^1_{cp_2}(Pg_2)=Pg_1^{\ 2}+2Pg_2^{\ 2}$

Subject to: $Pg_1+Pg_2=12$

Incorporating the power equations for the bus:

1. $Pg_1-Pd_1-t_{12}=0$, where $Pd_1=7 \therefore t_{12}=Pg_1-7$

2. $Pg_2-Pd_2-t_{21}=0$, where $Pd_2=5 \therefore t_{21}=Pg_2-5$

3. $t_{12}+t_{21}=0$

Overall the problem is to determine the operating points of gen1 and gen2 (Pg_1, Pg_2).

If you examine the original constraint, not separated, then the solution can be found easily with Lagrangian multipliers:

$L(Pg_1,Pg_2,\lambda)=Pg_1^{\ 2}+2Pg_2^{\ 2}+\lambda(Pg_1+Pg_2-12)$

$$\frac{\partial L(Pg_1,Pg_2,\lambda)}{\partial Pg_1}=\frac{\partial G^1_{cp_1}(Pg_1)}{\partial Pg_1}+\lambda=2Pg_1+\lambda=0 \Rightarrow \lambda=\frac{\partial G^1_{cp_1}(Pg_1)}{\partial Pg_1}$$

$$\frac{\partial L(Pg_1,Pg_2,\lambda)}{\partial Pg_2}=\frac{\partial G^1_{cp_2}(Pg_2)}{\partial Pg_2}+\lambda=4Pg_2+\lambda=0 \Rightarrow \lambda=\frac{\partial G^1_{cp_2}(Pg_2)}{\partial Pg_2}$$

$$\frac{\partial L(Pg_1,Pg_2,\lambda)}{\partial \lambda} = Pg_1 + Pg_2 - 12 = 0;$$

Method 1: Solving via Lagrangian Multipliers in a linear system, the partial derivatives produce 3 equations and 3 unknowns and can be solved directly via $Ax = b$.

Where $A = \begin{bmatrix} 2 & 0 & 1 \\ 0 & 4 & 1 \\ 1 & 1 & 0 \end{bmatrix}$, $x = \begin{bmatrix} Pg_1 \\ Pg_2 \\ \lambda \end{bmatrix}$, and $b = \begin{bmatrix} 0 \\ 0 \\ 12 \end{bmatrix}$ resulting in $x = \begin{bmatrix} Pg_1 \\ Pg_2 \\ \lambda \end{bmatrix} = \begin{bmatrix} 8 \\ 4 \\ -16 \end{bmatrix}$.

The generator operating points are determined to by 8 and 4, which satisfy the constraints with a value of $\lambda = -16$, which is where the gradients of both generator preferences are equal each other and λ.

$$\frac{\partial G^1_{cp_1}(Pg_1)}{\partial Pg_1} = 2Pg_1\Big|_{Pg_1=8} = 16 = \frac{\partial G^1_{cp_2}(Pg_2)}{\partial Pg_2} = 4Pg_2\Big|_{Pg_1=4} = -\lambda = -(-16) = 16$$

. The global cost function over values Pg_1, Pg_2 can be seen below with line of $Pg_1 + Pg_2 = 12$ and the solution at the lowest value of the function:

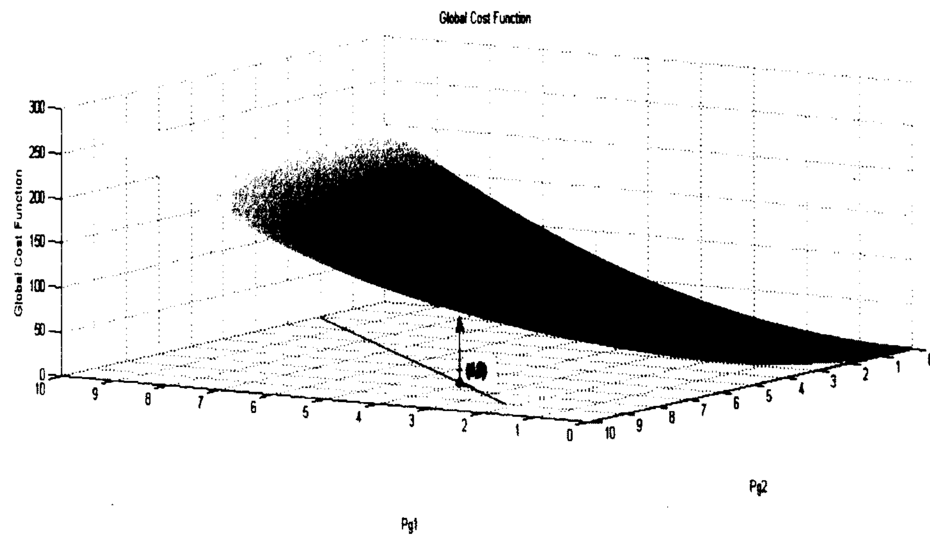

Figure 23: Graph of the Global Cost Function

Method 2: Taking another look at the minimization problem of the cost function, we examined the Lagrangian, $L(Pg_1, Pg_2, \lambda) = Pg_1^{\ 2} + 2Pg_2^{\ 2} + \lambda(Pg_1 + Pg_2 - 12)$. We know via the Weak Duality Theorem that the Lagrangian sub-problem

$h(\lambda) = \min L(x, \lambda) = \min L(Pg_1, Pg_2, \lambda) = \min[Pg_1^{\ 2} + 2Pg_2^{\ 2} + \lambda(Pg_1 + Pg_2 - 12)]$.

Using the Duality Theorems to find λ so that the largest lower bound is obtained by $\max(h(\lambda))$.

[Dual Problem]

Maximize over $\lambda(\min[Pg_1^{\ 2} + 2Pg_2^{\ 2} + \lambda(Pg_1 + Pg_2 - 12)])$.

Setting the partial derivatives equal to zero, Pg_1, Pg_2 can be written in terms of λ.

$$\frac{\partial L(Pg_1, Pg_2, \lambda)}{\partial Pg_1} = \frac{\partial G_{cp_1}^1(Pg_1)}{\partial Pg_1} + \lambda = 2Pg_1 + \lambda = 0 \Rightarrow Pg_1 = -\frac{\lambda}{2}$$

$$\frac{\partial L(Pg_1, Pg_2, \lambda)}{\partial Pg_2} = \frac{\partial G^1_{cp_2}(Pg_2)}{\partial Pg_2} + \lambda = 4Pg_2 + \lambda = 0 \Rightarrow Pg_2 = -\frac{\lambda}{4}$$

Substituting into the Dual Problem, we get:

Maximize over $\lambda(\min[Pg_1^2 + 2Pg_2^2 + \lambda(Pg_1 + Pg_2 - 12)])$ becomes,

Maximize over λ $[\left(-\frac{\lambda}{2}\right)^2 + 2\left(-\frac{\lambda}{4}\right)^2 + \lambda(\left(-\frac{\lambda}{2}\right) + \left(-\frac{\lambda}{4}\right) - 12)]$. The function $h(\lambda)$ is shown in Figure 24.

The maximum value of $h(\lambda)$ is found a value $\lambda = -16$, which then produces the solution obtained via the system of equations.

Method 3: The final look at this problem is via Lagrangian Relaxation where the constraint is relaxed and sub-problems are minimized over all possible values of Pg_1 and Pg_2:

$sbr1 = \min(G^1_{cp_1} + \lambda(Pg_1 - Pd_1)$

$sbr2 = \min(G^1_{cp_2} + \lambda(Pg_2 - Pd_2)$

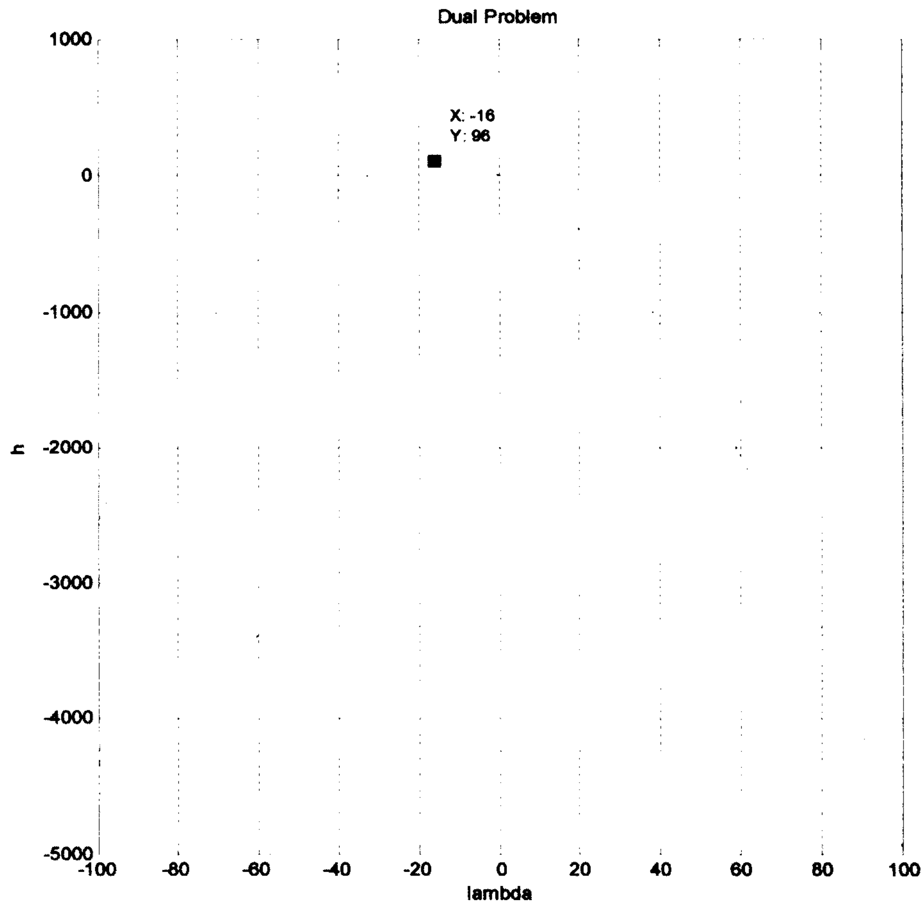

Figure 24: Dual Problem over Lambda

The algorithm converges quickly depending on the initial choice of λ to the solution as seen in Table 10.

The three methods provide different approaches to the same solution linking the concept of λ to the gradient of the cost functions. As different configuration and preferences are introduces, the original concept was to allow the transmission line

Lagrangian multiplier to change individually based upon the algorithms estimated constraint value of the transmission line.

Table 10: Solution to Method 3

subproblem	sbmin	Pg	Pd	gCost	λ
sb11	48	8	5	32	-16
sb21	48	4	6	64	-16

Constraints	
Line 1 - TP1	0
Line 1 - TP2	0

Total Minimum of Objective function	96

Thus as $t_{ij} + t_{ji}$ is calculated for every transmission line, the associated individual Lagrangian multiplier is allowed to adjust accordingly. Allowing the Lagrangian multipliers to adjust individually per time period is reflected in method 3; however Figure 18 demonstrates that each constraint can be equated to each other, resulting in a single constraint. Hence we can also utilize the algorithm to use a single Lagrangian multiplier per time period. If in fact, the demand and generation preferences do no change during the time periods considered and a single Lagrangian can be represented for all time periods. Hence two methods are examined in algorithm performance, the first when each transmission line in each period has an individual Lagrangian and the second when each time period has an individual

Lagrangian. A robust example is provided in a 6b3tp system, where demand is located within the loop and generation is external to the loop at buses 1, 4, and 6.

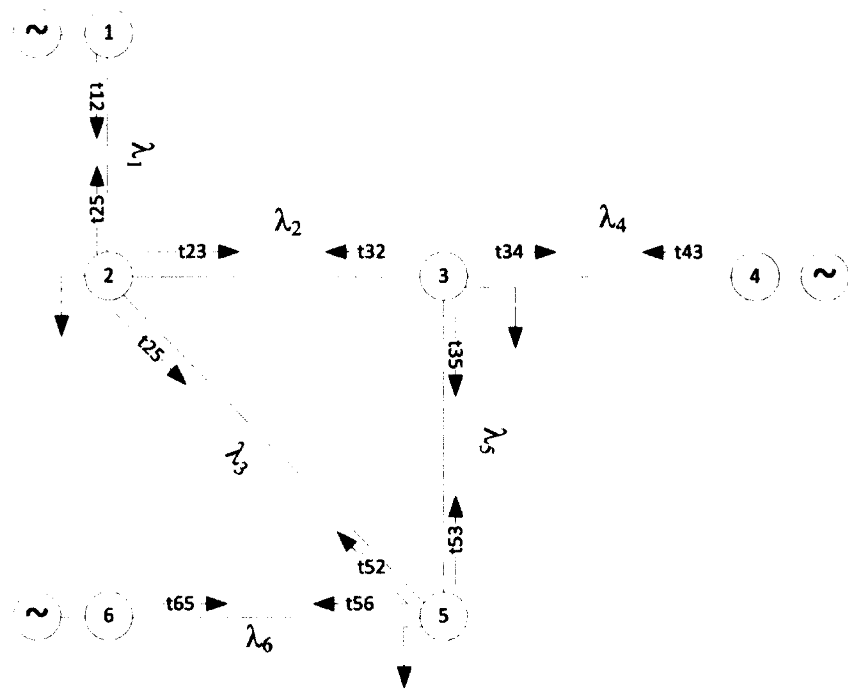

Figure 25: 6b3Tp Loop Configuration

In the configuration presented, Figure 25, the generation preference at bus 1 was lower than bus 4 and bus 6. Additionally the demand preferences were slightly lower at buses 2 and 5 than at bus 3. Finally bus 5 has an energy constraint $E_5 = 21$ kWh. This configuration was used for both methods. The algorithm using a single Lagrangian multiplier for the system converged in fewer steps than the other method of varying individually. In all the cases examined the iteration of the single Lagrangian case were less than or equal to the varied Lagrangian case. In the simplest example when the number of transmission lines is equal to 2, the number of iterations of each case is equal. The individually varied case increased in iterations as the system size grew, a reflection of the estimation of t_{ij} from the delta function for internal nodes. It should be noted that the convergence of the individual transmission line Lagrangian, λ_i, shows a migration of each individual Lagrangian to a single value as the algorithm converges to a global minimum. This was further amplified by the requirement of an energy constraint or capacity constraint (discussed later). In other words, as agent within the system estimates t_{ij} based upon its neighbors, the effect of not knowing the true value affected the convergence of the individual Lagrangian during the single time period. These extra iterations to converge during the single time period were then multiplied by the addition of an energy constraint or transmission line capacity constraint placed on the system. The nuances of these two different approaches could provide some insight to distributed control implementation, and this is reserved for later investigation. The results from the 6b3Tp example with and without energy constraints are presented in Table 12. .

Table 11: Single Lagrangian vs varied Lagrangians - No Energy Constraint

Single Lagrangian

sbprm	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	-5.383	16.4	0	5.379	0	-0.656	0
sb21	-5.383	16.4	0	5.379	0	-0.656	0
sb31	-5.383	16.4	0	5.379	0	-0.656	0
sb12	6.025	0	8.4	0	0.512	-0.656	0
sb22	6.025	0	8.4	0	0.512	-0.656	0
sb32	6.025	0	8.4	0	0.512	-0.656	0
sb13	8.532	0	9.6	0	2.232	-0.656	0
sb23	8.532	0	9.6	0	2.232	-0.656	0
sb33	8.532	0	9.6	0	2.232	-0.656	0
sb14	-1.615	4.9	0	1.601	0	-0.656	0
sb24	-1.615	4.9	0	1.601	0	-0.656	0
sb34	-1.615	4.9	0	1.601	0	-0.656	0
sb15	6.025	0	8.4	0	0.512	-0.656	0
sb25	6.025	0	8.4	0	0.512	-0.656	0
sb35	6.025	0	8.4	0	0.512	-0.656	0
sb16	-1.615	4.9	0	1.601	0	-0.656	0
sb26	-1.615	4.9	0	1.601	0	-0.656	0
sb36	-1.615	4.9	0	1.601	0	-0.656	0

Global Minimum for the system: 35.51
Iterations 7

Varied Lagrangians

sbprm	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	-5.256	16.2	0	5.249	0	-0.6484	0
sb21	-5.256	16.2	0	5.249	0	-0.6484	0
sb31	-5.256	16.2	0	5.249	0	-0.6484	0
sb12	5.918	0	8.4	0	0.512	-0.8438	0
sb22	5.918	0	8.4	0	0.512	-0.8438	0
sb32	5.918	0	8.4	0	0.512	-0.8438	0
sb13	9.266	0	9.6	0	2.232	-0.5313	0
sb23	9.266	0	9.6	0	2.232	-0.5313	0
sb33	9.266	0	9.6	0	2.232	-0.5313	0
sb14	-1.937	5.4	0	1.944	0	-0.7188	0
sb24	-1.937	5.4	0	1.944	0	-0.7188	0
sb34	-1.937	5.4	0	1.944	0	-0.7188	0
sb15	4.96	0	8.7	0	0.338	-0.5313	0
sb25	4.96	0	8.7	0	0.338	-0.5313	0
sb35	4.96	0	8.7	0	0.338	-0.5313	0
sb16	-1.937	5.4	0	1.944	0	-0.5313	0
sb26	-1.937	5.4	0	1.944	0	-0.5313	0
sb36	-1.937	5.4	0	1.944	0	-0.5313	0

Global Minimum for the system: 36.656
Iterations 11

Table 12: Single Lagrangian versus varied Lagrangians- Energy Constraint

Single Lagrangian

sbprm	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	-5.006	15.8	0	4.993	0	-0.6328	0
sb21	-5.006	15.8	0	4.993	0	-0.6328	0
sb31	-5.006	15.8	0	4.993	0	-0.6328	0
sb12	5.828	0	8.4	0	0.512	-0.6328	0
sb22	5.828	0	8.4	0	0.512	-0.6328	0
sb32	5.828	0	8.4	0	0.512	-0.6328	0
sb13	8.306	0	9.7	0	2.168	-0.6328	0
sb23	8.306	0	9.7	0	2.168	-0.6328	0
sb33	8.306	0	9.7	0	2.168	-0.6328	0
sb14	-1.502	4.7	0	1.473	0	-0.6328	0
sb24	-1.502	4.7	0	1.473	0	-0.6328	0
sb34	-1.502	4.7	0	1.473	0	-0.6328	0
sb15	10.167	0	7	0	1.8	-0.6328	0.563
sb25	10.167	0	7	0	1.8	-0.6328	0.563
sb35	10.167	0	7	0	1.8	-0.6328	0.563
sb16	-1.502	4.7	0	1.473	0	-0.6328	0
sb26	-1.502	4.7	0	1.473	0	-0.6328	0
sb36	-1.502	4.7	0	1.473	0	-0.6328	0

Global Minimum for the system: 37.254
Iterations 38

Varied Lagrangians

sbprm	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	-4.883	15.6	0	4.867	0	-0.625	0
sb21	-4.883	15.6	0	4.867	0	-0.625	0
sb31	-4.883	15.6	0	4.867	0	-0.625	0
sb12	10.211	0	9.1	0	0.162	1.0313	0
sb22	10.211	0	9.1	0	0.162	1.0313	0
sb32	10.211	0	9.1	0	0.162	1.0313	0
sb13	-6.807	0	10	0	2	-0.7656	0
sb23	-6.807	0	10	0	2	-0.7656	0
sb33	-6.807	0	10	0	2	-0.7656	0
sb14	-1.465	4.7	0	1.473	0	1.5938	0
sb24	-1.465	4.7	0	1.473	0	1.5938	0
sb34	-1.465	4.7	0	1.473	0	1.5938	0
sb15	10.222	0	7	0	1.8	-0.7656	0.438
sb25	10.222	0	7	0	1.8	-0.7656	0.438
sb35	10.222	0	7	0	1.8	-0.7656	0.438
sb16	-2.198	5.7	0	2.166	0	-0.766	0
sb26	-2.198	5.7	0	2.166	0	-0.766	0
sb36	-2.198	5.7	0	2.166	0	-0.766	0

Global Minimum for the system: 37.404
Iterations 84

CONVEX FUNCTIONS AND IMPROVING THE ALGORITHM

Previous three different approaches to solving the global minimization problem have been examined. Two of these approaches are derived from methodologies which include requirements for the function in the global problem to be convex over the domain. These methods do not guarantee a solution when a function is not convex. There is a slight advantage in the Relaxation method where, in the sub-problem every value of the generation preference function is evaluated against every value of the demand preference function by a brute force approach. This shows improvement when functions are not convex, however other problems arise when making determinations in the sub-problem, quantizing error, and step-size error in the Lagrangian multipliers. Under certain conditions the algorithm will 'bounce' and be unable to converge to a solution. Adjusting different parameters which effect convergence, quantizing, and decision within the sub-problem can sometimes reduce the 'bouncing' of the algorithm and help convergence. The steps are reasonable and help raise the questions of the accuracy and methodology of determining convergence. For example in a system of 100 units of generation, what is an acceptable level of accuracy to find convergence? What is the tolerance level of transmission line mismatch or in meeting energy constraints? In practice during the evaluation of different systems, this parameter was examined, and as mentioned earlier as a discussion of 'tightening up' of the system. The direct effect of the 'tightening up' of the parameters related to accuracy, quantizing, and decision within the sub-problem was the number of iterations of the algorithm ,if it converged at all. Meaning it was routinely possible to adjust one parameter that directly forced other parameters outside their effectiveness. One example of this would be to reduce the error required for in the algorithm for a transmission line constraint to be met without adapting the limits associated with the adjustment of the Lagrangian multiplier associated with that transmission line. In this condition the system was looking for a better solution based upon a lower mismatch on the transmission line without being able to adjust the Lagrangian multiplier associated with that transmission line. Hence convergence speed, error, and adjusting parameters are a balancing act based upon each system and topology. Without saturating the reader with excruciating details, suffice it to say that a change in topology, fixed demand, step-size of generation or demand, or changing the number of buses with no generation or demand affects the algorithm ability to narrow the solution.

Given this effect of the Relaxation method to changes described above the concept of "Convexification' was considered and investigated for a possible improvement in the algorithm. The algorithm demonstrates that under conditions where quantizing error in step-size of demand, generation, or Lagrangian multipliers were mismatched to the gradients of generation or demand preference functions created the "bouncing" effect. This description is not easily quantifiable or scientific, however it represents a property of the implemented algorithm. To compensate for this characteristic a term was added to the sub-problem to suppress the conditions that created the bouncing effect, essentially adding a convex property to the sub-problems. Remember that the original sub-problem consisted of the local problem at each bus_i and TP_n : $G^n_{CP_i} + D^n_{CP_i} + \sum_{k=1}^{p} \lambda^n_k (Pg^n_i - Pd^n_i) + \mu_i (Pd^n_i)$, where p is the number of the associated transmission lines. The following term was added to the local sub-problem: $\sum_{k=1}^{p} cxi_k (t_{im} + t_{mi})^2$. This term is a summation of a scalar (cxi_k) times the square of the mismatch on each associated transmission line. Hence as the mismatch for each transmission line associated with each bus is calculated through the algorithm, it is squared, and added to the local sub-problem. This technique presented some advantage in different topologies, however in other topologies it did not. In a 3bus3tp example the technique demonstrated improvement convergence time with small error in the global minimum as well as values of Pg and Pd for the system. Table 13 represents the results from a 3b2tp system, where cxi was set to 0, 1, and 10. A value of $cxi = 0$ is equivalent to not having the term in the sub-problem. The significant result in Table 3 is the 75% reduction in iterations of the algorithm with a largest increase in error at the most interior bus where Pg and Pd differed by the largest amount. Comparing this to a 5 bus radial system where a large value of cxi caused the system to bounce where previously a value of $cxi = 0$ did not. However after tuning or "loosening" constraints the 5b2tp system quickly converged to a slightly different solution with the largest differences at the interior buses as previously mentioned before (Table 14). To validate the changes cxi was set to zero and the other changes were maintained. This provided a solution where the convergence of the algorithm required a significantly larger number of iterations.

Overall the convexing function added to the sub-problem introduced another tuning parameter that in some circumstances can improve the convergence of the algorithm, however just as the other tuning parameters can cause the problem to worsen so can the convexing function. A list of the larger tuning parameters is provided in Appendix A.

Table 13: Performance of Convexing function 3b3tp

		Case			% Diff	
		cxi=0	cxi=1	cxi=10	cxi=1	cxi=10
	Iteration	32	22	8	-31.25%	-75.00%
Pg1	Tp1	4.6	4.7	5	2.17%	8.70%
	Tp2	4.6	4.7	5	2.17%	8.70%
	Tp3	4.6	4.7	5	2.17%	8.70%
Pg2	Tp1	2.7	2.6	2.2	-3.70%	-18.52%
	Tp2	2.7	2.6	2.2	-3.70%	-18.52%
	Tp3	2.7	2.6	2.2	-3.70%	-18.52%
Pg3	Tp1	4.6	4.7	5	2.17%	8.70%
	Tp2	4.6	4.7	5	2.17%	8.70%
	Tp3	4.6	4.7	5	2.17%	8.70%
Pd1	Tp1	4	4	4	0.00%	0.00%
	Tp2	4	4	4	0.00%	0.00%
	Tp3	4	4	4	0.00%	0.00%
Pd2	Tp1	3.9	3.9	4.1	0.00%	5.13%
	Tp2	3.9	3.9	4.1	0.00%	5.13%
	Tp3	3.9	3.9	4.1	0.00%	5.13%
Pd3	Tp1	4	4	4	0.00%	0.00%
	Tp2	4	4	4	0.00%	0.00%
	Tp3	4	4	4	0.00%	0.00%
cp1	Tp1	-1.8281	-1.875	-2	2.57%	9.40%
	Tp2	-1.8281	-1.875	-2	2.57%	9.40%
	Tp3	-1.8281	-1.875	-2	2.57%	9.40%
cp2	Tp1	-1.8281	-1.8281	-2	0.00%	9.40%
	Tp2	-1.8281	-1.8281	-2	0.00%	9.40%
	Tp3	-1.8281	-1.8281	-2	0.00%	9.40%
dv1	Tp1	0	0	0.05	0.00%	5.00%
	Tp2	0	0	0.05	0.00%	5.00%
	Tp3	0	0	0.05	0.00%	5.00%
dv2	Tp1	0	0	0.05	0.00%	5.00%
	Tp2	0	0	0.05	0.00%	5.00%
	Tp3	0	0	0.05	0.00%	5.00%
Global Minimum		39.186	39.772	40.384	1.50%	3.06%

Table 14: Performance of Convexing function 5b2tp

		Case		% diff
		cxi=0	cxi=10	cxi=10
	Iteration	124	8	-93.55%
Pg1	Tp1	3	1.7	-43.33%
	Tp2	3	1.7	-43.33%
Pg2	Tp1	3.5	3.5	0.00%
	Tp2	3.5	3.5	0.00%
Pg3	Tp1	3	4.9	63.33%
	Tp2	3	4.9	63.33%
Pg4	Tp1	1.8	0.6	-66.67%
	Tp2	1.8	0.6	-66.67%
Pg5	Tp1	10	10	0.00%
	Tp2	10	10	0.00%
Pd1	Tp1	0	0	0.00%
	Tp2	0	0	0.00%
Pd2	Tp1	6	5.9	-1.67%
	Tp2	6	5.9	-1.67%
Pd3	Tp1	7.1	7.3	2.82%
	Tp2	7.1	7.3	2.82%
Pd4	Tp1	8.1	7.9	-2.47%
	Tp2	8.1	7.9	-2.47%
Pd5	Tp1	0	0	0.00%
	Tp2	0	0	0.00%
Global Minimum		136.344	132.612	-2.74%

EXAMINING IMPLEMENTATION

The formulation presented is essentially an optimal power flow in disguise. It uses power flow constraints and even implements a "dc like" power flow guess into the bus. However, it moves beyond the power flow by taking a further step in the direction of energy delivery by providing a formulation which incorporates input from producers and consumers. A vision of how this could be implemented needs presented. From the formulation, the concept of an agent located on a point of common coupling manages energy toward the network and instantaneous power locally. The agent learns the energy habits of the local area by managing local instantaneous power via energy assets (demand, storage, generation) and input from users. The agent communicates the determined energy requirements to the network by responding to information from the network. The habits can be interpreted as energy needs, generation preferences, and demand preferences which are known locally and acted upon to solve the global objective along with local objectives (the sub-problem). You can interpret the communication in the form of a Lagrangian multiplier which can be communicated from a transmission line agent to the local agent. The response from the local agent is simply its demand and/or generation based upon its preference functions and its local solution to the sub-problem. It is the up to the transmission line agent to make a constraint decision for each time period and total event horizon. The constraint decision then results in a change in the value of the Lagrangian value with a re-transmission of the Lagrangian or a final solution for the system or agent.

The question of how is this formulation different than a price signal sometimes arises. The communication of the Lagrangian multiplier to the agent and its response has a similar communication flow as a price signal scheme. However this formulation goes beyond a price signal scheme and a power flow. The formulation searches for a global cost minimum as well as determining operating points of the power system based upon preferences over time and can be solved in a distributed or centralized structure. Additionally it demonstrates a robust method of introducing different constraints that can be implemented in the same fashion as the transmission line, energy, and capacity Lagrangians. Hence the formulation has a price signal characteristic, but includes a power flow with input for each bus based upon preferences and constraints.

Examining demand and energy information over a time horizon intuitively allows the generators to adjust output over all the time periods. Local agents feed preference information via a response to a Lagrangian multiplier into the network through the transmission line agents. The concept of information of generation as well as demand adjusting based upon a preference is in contrast to how electrical energy is used today. The underlying fact is that in an implementation of this algorithm, demand is now adjusting quickly to changes in the network, a desired feature of the smart grid.

The significance demonstrated in the algorithm is the formulation supports the communication of information required for each agent within the system to solve local optimization problem based upon individual preferences (demand, generation, energy) leading to operating points within the microgrid. Additionally the methodology presented is open to communication and processing architectures that are distributed, hierarchal, or centralized.

Overall the traditional power system would change significantly if the instantaneous power requirement responsibility shifts to the user, information is exchanged, and markets or bidding systems are established between buses based upon demand preferences, generation preferences, and energy requirements; which is exactly what this algorithm represents. It is foreseeable to have the bus agent managing energy requirements into the network and power requirements locally by managing energy assets, just as "NEST" thermostat today learns the occupants habits and preferences and then acts on them to meet requirements, learning all along. Performance could be fed back to the agent after each time period based upon its committed resources and what actually occured. The sensitivity could be based upon the user's reliability expectation which could affect the response of the agent and extent of energy assets.

In the assessment of different preference functions the generation preference functions more direct and simpler to discuss. One could translate fixed and variable cost directly to a cost per kWh function based upon output. Thus provide different generation preference functions based upon current market cost for generation including DOE 2020 cost targets. Fuel was allowed as a variable in the configuration spreadsheets. Additionally, specific polynomials could be entered if desired. Renewables had to be looked in a different manner, as fuel cost was not generally a factor. Hence a generation function could be the output of a solar inverter where fixed costs are trying to be recovered. In this situation an agent may have to be compensated not to put out maximum generation which would be the preference in hopes of recovering fixed costs. This type of generation function could have opposite characteristics of the typical generation function based upon conventional generation.

In a more challenging process demand preferences represent the willingness of an agent to service its demand. It is useful to consider the concept of demand preference as a commercial entity, where energy is factored into the cost of business. Here a map of energy needs and cost willingness on the behalf of the commercial entity can be communicated by the agent. The understanding and identification of demand and energy is the foundation of any demand preference. For example, a steel plant can base its willingness to pay at what demand level based upon a market condition and business needs. Hence the customer is developing a demand preference, which direct effect is the flattening of the generation and demand profiles.

To associate the residential side of electrical energy use, the concept of an agent learning habits and requirements similar to the "NEST" thermostat is an example of how the demand preference could be communicated, but what that preference function looks like is unique to the individual. However the single most important concept was that there is no right generation function or demand function.

In fact, a strength of the brute force Lagrangian Relaxation technique is that every value of the preference functions are examined for the minimum cost function locally. It should be noticed that the other methods demonstrated rely on convex function for derivatives, which could be a limiting factor of demand and generation preference functions. The Lagrangian Relaxation method provides for brute force computer calculations and the ability to "help" convexity problems.

The discussion of how the algorithm can relate to market inter-working has been a question of interest. Today in the U.S., utilities operate monopolies regulated under the 4th Amendment of the Constitution. Costs are examined under rate cases and regulatory bodies review and determine rates. In addition to determining rates, public commissions also implementation policy through rates and requirements of regulated service providers. The idea presented here is not intended to be an argument for policy, but simply a discussion of a potential implementation of the factors within the algorithm that can affect cost and payments. As discussed earlier, this methodology is more than just a price signal. In market settlement for a price signal, actual costs are easily calculated once the price is established. However in this algorithm price and cost are not as straight forward. The Lagrangian multipliers, constraints, and preference function can become factors in market settlement and help identify costs. In general generation preferences can be thought of a cost function which may reflect fixed costs, variable costs, and profit. These costs are more apparent as they are a direct result of a generation preference function. Upon completion of the algorithm each bus has the final transmission line Lagrangian multiplier. This Lagrangian evaluated in the local sub-problem provides operating points and the generation cost based upon the preference function. This can be accomplished at every bus, thus all generation costs and generation outputs are known.

The demand costs are not as easy to associate as true costs. Demand cost reflect a relative desire to have demand met at some cost level which may or may not be associated to market costs. Hence a market clearing methodology should examine the generation cost component of the global minimum. If we utilize a market clearing formulation by using Lagrangian of the time period to determine demand payments the advantages of the Energy Delivery Paradigm can be readily seen. To accomplish this we establish a market structure where payments are made for electrical energy based upon energy consumed and the associated Largangian multipliers of the bus. Hence a bus individually calculates via the sub-problem its financial contribution for the system. If we use a 3 bus 4 time period system (3b4tp) where Bus1 and Bus3 are demand buses and Bus2 is a generation bus (Figure 26) we can establish 3 cases to illustrate the market clearing and financial benefits to the Energy Delivery Paradigm.

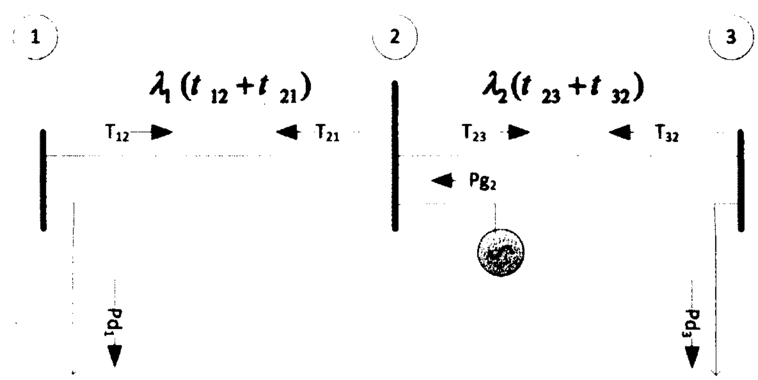

Figure 26: 3b4tp Market Clearing Example

In all the cases the generation and demand preferences do not change.

Case 1: Bus 1 and Bus 3 represent varying demand during each time period, which are represented in Table 15.

Table 15: Market Clearing Case 1 Demand

	Demand		
	Bus 1	Bus 3	
Time Period 1	8	9	kW(Δt)
Time Period 2	2	2	kW(Δt)
Time Period 3	10	9	kW(Δt)
Time Period 4	2	2	kW(Δt)

Case 2: Bus 1 continues the varying demand, however for Bus 3 instead of requiring varying demand, Bus 3 provides the system with an energy constraint for the same about of energy in Case 1. E_3 for the algorithm is set to $22kW\Delta t$

Table 16: Market Clearing Case 2- Energy Constraint

	Demand		
	Bus 1	Bus 3	
Time Period 1	8	E3	kW(Δt)
Time Period 2	2	E3	kW(Δt)
Time Period 3	10	E3	kW(Δt)
Time Period 4	2	E3	kW(Δt)
E3 represent the Energy Constraint of bus 3			

Case 3: Bus 1 and Bus 3 represent energy requirements equal to case 1, hence E_1 is $22kW\Delta t$ and is $22kW\Delta t$.

Table 17: Market Clearing Case 3

	Demand		
	Bus 1	Bus 3	
Time Period 1	E_1	E_3	kW(Δt)
Time Period 2	E_1	E_3	kW(Δt)
Time Period 3	E_1	E_3	kW(Δt)
Time Period 4	E_1	E_3	kW(Δt)
E1 andE3 - Energy Constraint demand buses			

For Case 1 we see that each of the time period fixed demand is met for each bus and the overall system generation costs are $9.82. Using the methodology discussed for market clearing the energy costs for each bus are calculated based upon the Lagrangian for each transmission line. In this case, $|\lambda| = 0.25$, and the associated energy cost per time period are calculated. The results show that in Case 1 the unit cost per energy is $0.25 for each bus (Table 18). If we now examine these cost versus Case 2, where Bus3 provides an energy constraint for the system versus fixed values (Table 16), the results show the overall generation cost for the system are $9.58 and the unit cost per energy is $0.2187 for Bus3 and $0.2378 for Bus1. The overall system costs are reduced and the energy cost for each bus is also reduced with Bus3 experiencing the most reduction in cost. This raises and interesting point where the energy constraint at Bus3 is helping reduce the cost per unit energy of Bus1, this is a derivative of the local bus contributing to the global system minimum which helps the entire system. In other words Bus3 is contributing to the system minimization which helps reduce the costs at Bus1.

Table 18: Case 1 Market Clearing Results

subproblem	Pg	Pd	gCost	cp	Energy Costs	Cost per Unit of TP's
sb11	0	8	0	-0.25	2	0.2500
sb21	0	2	0	-0.25	0.5	
sb31	0	10	0	-0.25	2.5	
sb41	0	2	0	-0.25	0.5	
sb12	17	0	3.58		0	
sb22	4	0	1.098		0	
sb32	19	0	4.039		0	
sb42	4	0	1.098		0	
sb13	0	9	0	-0.25	2.25	0.2500
sb23	0	2	0	-0.25	0.5	
sb33	0	9	0	-0.25	2.25	
sb43	0	2	0	-0.25	0.5	

One additional method of reflecting system contribution could be to include in the formulation a factor of the Lagrangian multiplier associated with the energy constraint at each bus. Under this method further incentive can be given to contributing agents within the system. The goal here is not debate the different methods that could work in the market clearing, but just to represent the effects and potentials of the system.

The results from Case 3, show that the effect Bus 1 and Bus 3 having energy constraints drive the system generation cost even lower to a value of $9.47 and corresponding cost per unit energy of $0.188 for both Bus 1 and Bus2.

Overall it is easy to see in a market clearing example how participating in the market presented with an energy constraint can reduce the cost per unit of energy for a single bus and improve the overall system cost. Both of these traits are important to the Energy Paradigm, as not every participant of a microgrid will be able to participate with and energy constraint.

Table 19: Case 2 Market Clearing Results

subproblem	Pg	Pd	gCost	cp	Energy Costs	Cost per Unit of TP's
sb11	0	5.5	0	-0.188	1.034	
sb21	0	5.5	0	-0.188	1.034	0.1880
sb31	0	5.5	0	-0.188	1.034	
sb41	0	5.5	0	-0.188	1.034	
sb12	11	0	2.368		0	
sb22	11	0	2.368		0	
sb32	11	0	2.368		0	
sb42	11	0	2.368		0	
sb13	0	5.5	0	-0.188	1.034	
sb23	0	5.5	0	-0.188	1.034	0.1880
sb33	0	5.5	0	-0.188	1.034	
sb43	0	5.5	0	-0.188	1.034	

Table 20: Market Clearing Results Case 3

subproblem	Pg	Pd	gCost	cp	Energy Costs	Cost per Unit of TP's
sb11	0	8	0	-0.25	2	
sb21	0	2	0	-0.188	0.376	0.2387
sb31	0	10	0	-0.25	2.5	
sb41	0	2	0	-0.188	0.376	
sb12	13.45	0	2.828		0	
sb22	7.5	0	1.761		0	
sb32	15.4	0	3.229		0	
sb42	7.5	0	1.761		0	
sb13	0	5.4	0	-0.25	1.35	
sb23	0	5.5	0	-0.188	1.034	0.2187
sb33	0	5.4	0	-0.25	1.35	
sb43	0	5.5	0	-0.188	1.034	

Benefit is seen for the system as a whole as soon as one bus participates with an energy constraint. In the results presented actual internal combustion engine efficiency curves were utilized to build the generation preference curves and include fuel and O&M costs. The examples were extended to 24 time periods to show a longer time period graph representing the influence of the energy constraint. Figure 27 represents the cost of energy per time period of Bus1 and Bus3 over 24 time periods for 3 cases. Case 1: Fixed demand at bus 1 and bus 3; Case 2: Fixed demand at one bus and energy constraint at other; Case 3: Energy constraints at both buses. The smoothing and lowering of overall all cost is apparent as well as the reduction in cost per unit of energy represented by Figure 28. Finally Figure 29 represents the overall cost per unit energy for the each bus during the entire 24 time periods.

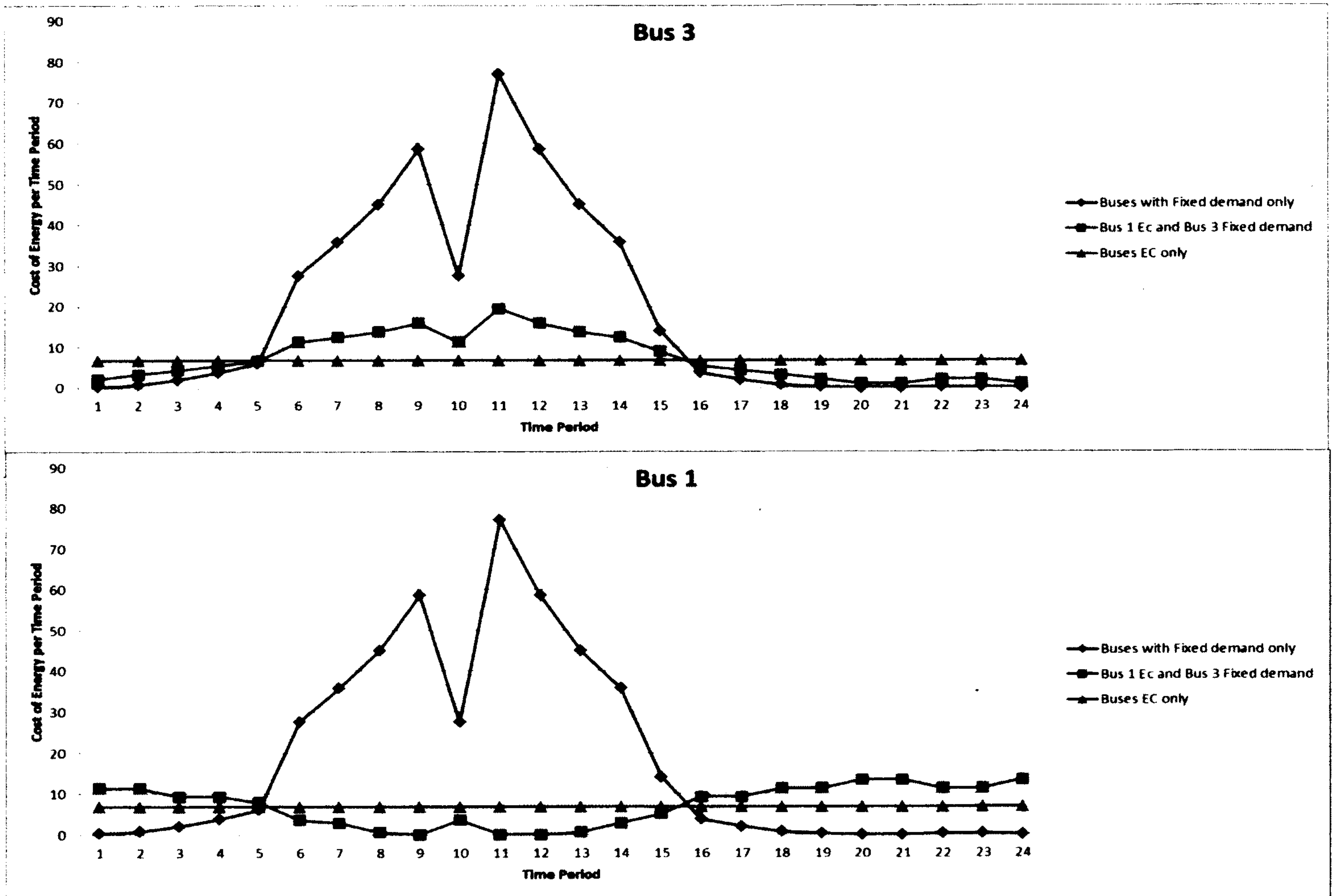

Figure 27: 3b24tp Cost Of Energy per TP

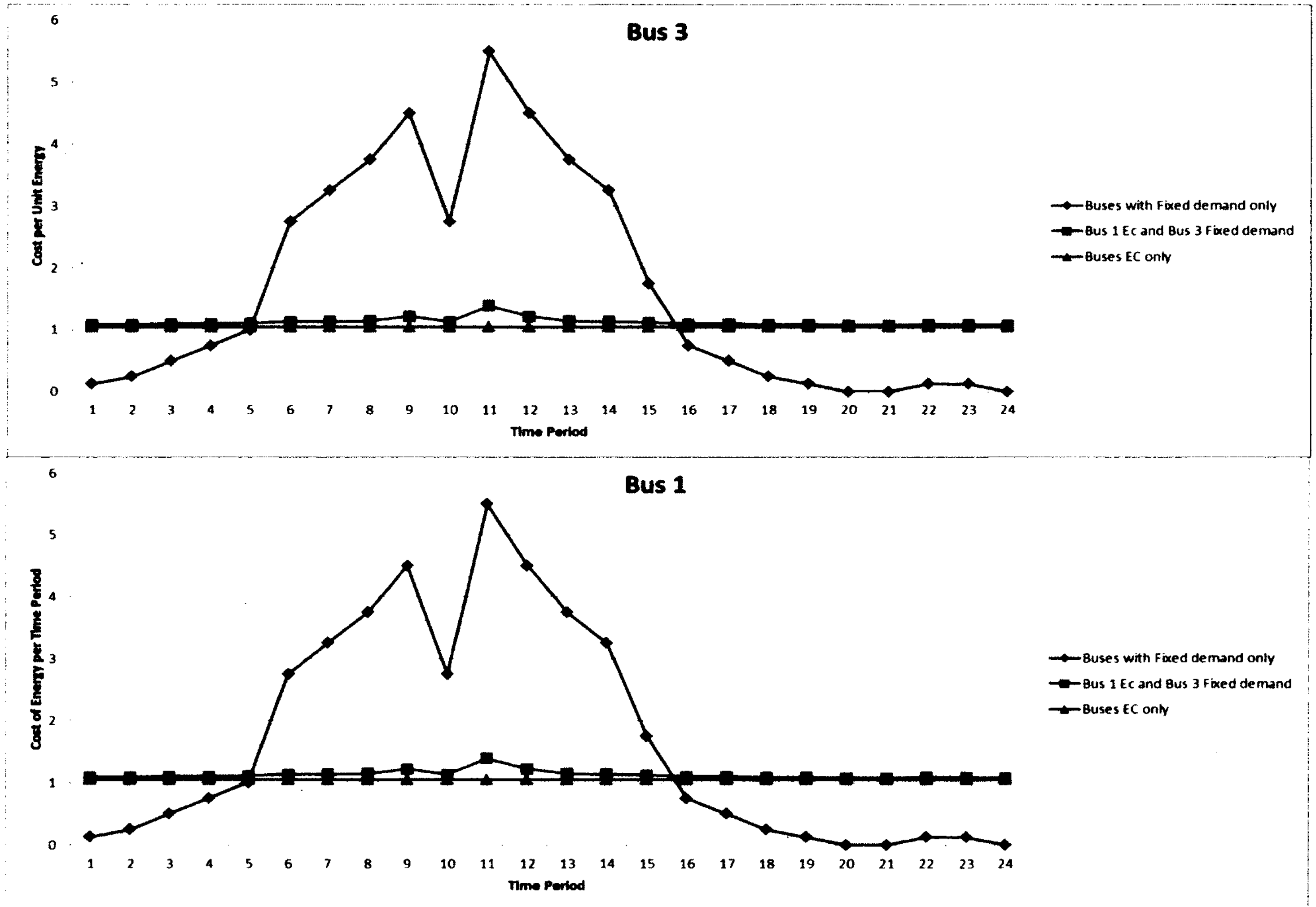

Figure 28: 3b24tp Cost per Unit Energy

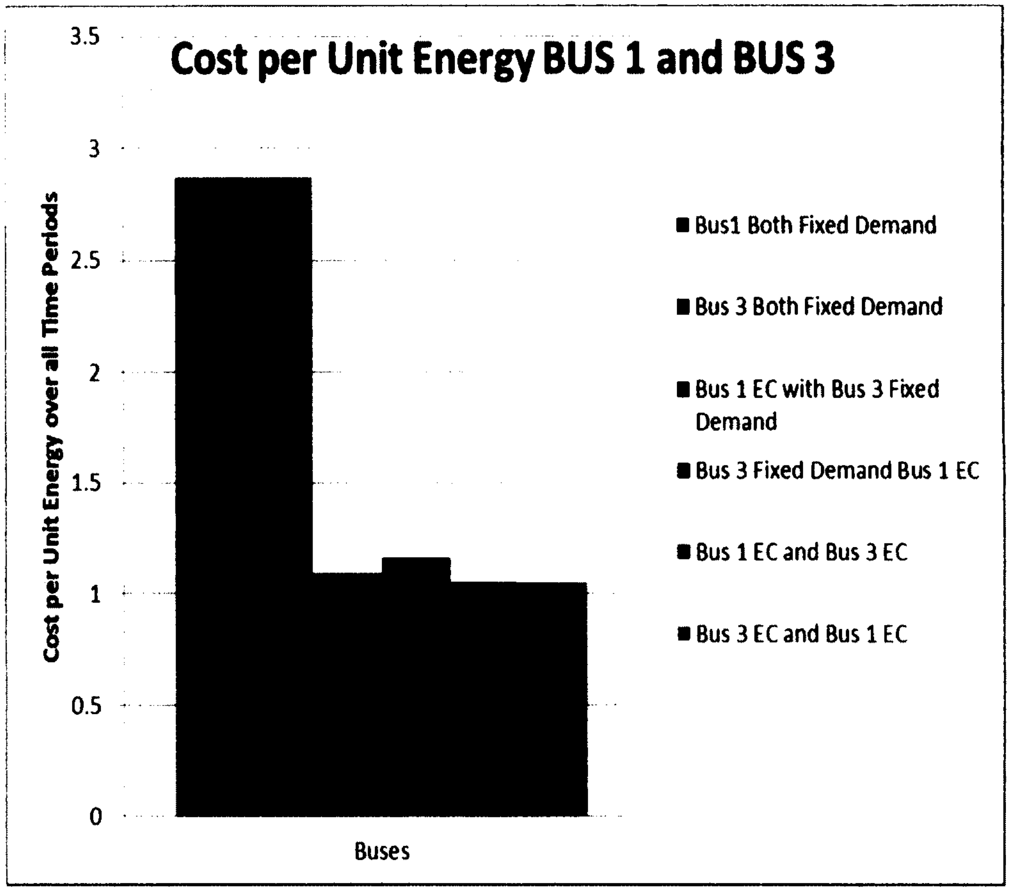

Figure 29: Effects of Energy Constraint on Cost Per Unit Energy

The principal discussed early in the document was that the dichotomy between usage and sustainability. The energy delivery paradigm here presents a set of concepts that demonstrate the benefits of energy constraints which represent a change to the way we currently use energy in the U.S. Both demand preference and energy constraints provide a platform for the consumer to actively participate with producers in and energy market allowing a shift in how we electricity.

Overall any implementation success will depend upon the ability of local agents to accurately communicate energy requirements and manage local instantaneous power with energy assets. Hence we will need to watch how microgrid controls, energy storage, and commissions progress.

ENERGY PARADIGM EFFECT

Previously it has been represented that the energy paradigm can help generators run at higher efficiency due to flattening of the demand curve. It is important to point out the mechanisms within the algorithm and actors that contribute to this. Two important mechanisms are the preference functions and energy constraints. The demand preference function represents a response to the generator preference in the minimization problem and the energy constraint allows for the overall energy delivered to be accomplished at the minimum cost level within the formulation.

To see the interactions of energy constraint we examine a three bus system, Bus2 has generation and Bus1 and Bus3 have demand, (Figure 30). We examine this system over twenty-four hours broken into three segments, representing peak and off peak times during the day. The first segment is hours 0-5, the second is hours 6-17, and the third is hours 18-23. The system is examined in two difference cases to demonstrate the energy effect.

Case 1: Varying demand. The demand at Bus1 and Bus3 are set to varying fixed values and the generator output at Bus2 is examined.

Case 2: Energy Constraints: Bus1 and Bus3 require the same energy as in case 1, for each of the time segments. Hours 0-5: $E_1 = 41, E_3 = 74$, hours 6-17: $E_1 = 130, E_3 = 97$, hours 18-23: $E_1 = 17, E_3 = 47$.

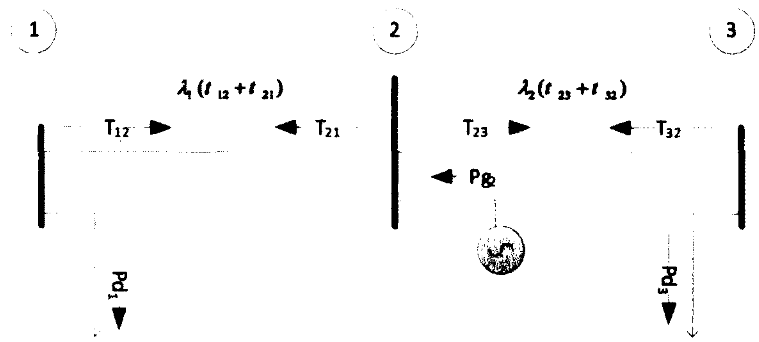

Figure 30: 3b3Tp Energy Example

Case 1 results show us that without the energy constraint, the generator follows the changing load to satisfy the power flow. Case 2 shows us that the same amount of energy is delivered during the 3 segments; however the generator output is constant.

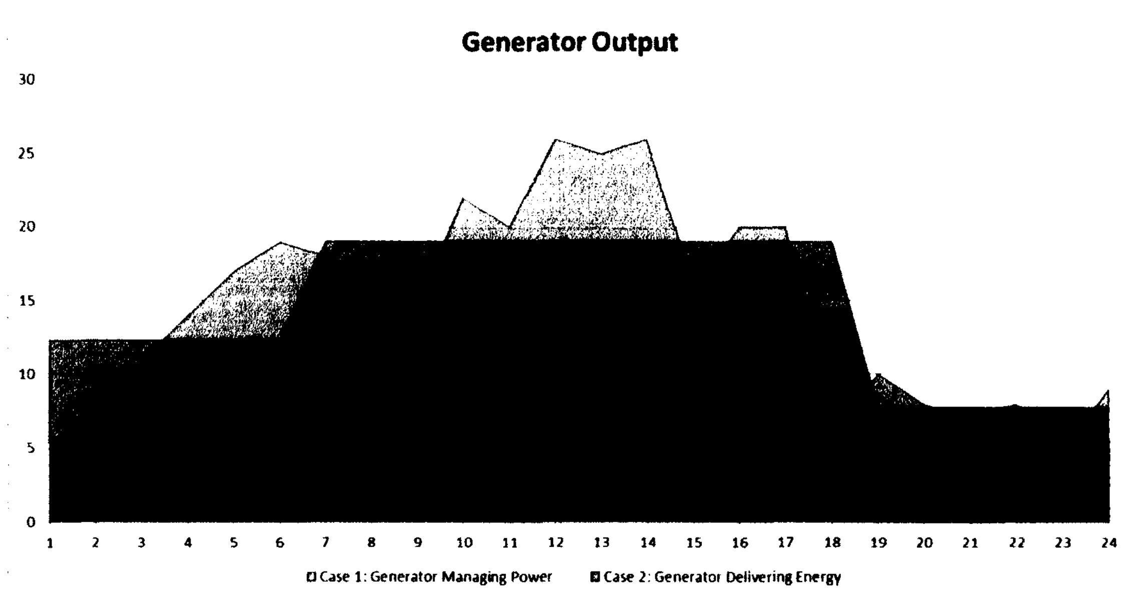

Figure 31: Varying Demand versus Energy Constraint

In another example we examine how the demand preferences contribute to this effect by starting with demand preferences on all buses and then moving to varying demand. For this a 5bus3tp system, Figure 32, is configured. In this configuration all buses have generation and demand preferences. Each generation preference is different, with bus 5 having the lowest cost preference and bus 1 having the highest cost preference. The demand preferences are equivalent for bus 1, bus3, and bus5, while bus2 and bus4 are equivalent. The result of this configuration shows that the output of the generators remain constant for each of the 3 time periods (Table 23).

This example provides a good baseline against the next problem where demand is fixed for each time period, representing varying demand. To illustrate the effect of the algorithm on generation we fix the demand at Bus1 and Bus3 and change it over each time period.

Configuration:

- Bus1 demand is 4, 5, and 6 for time periods 1, 2, and 3 respectively.

-Bus3 demand is 5, 6, and 7 for time periods 1, 2, and 3 respectively.

-Bus2 and bus 4 have energy constraints of 18 each.

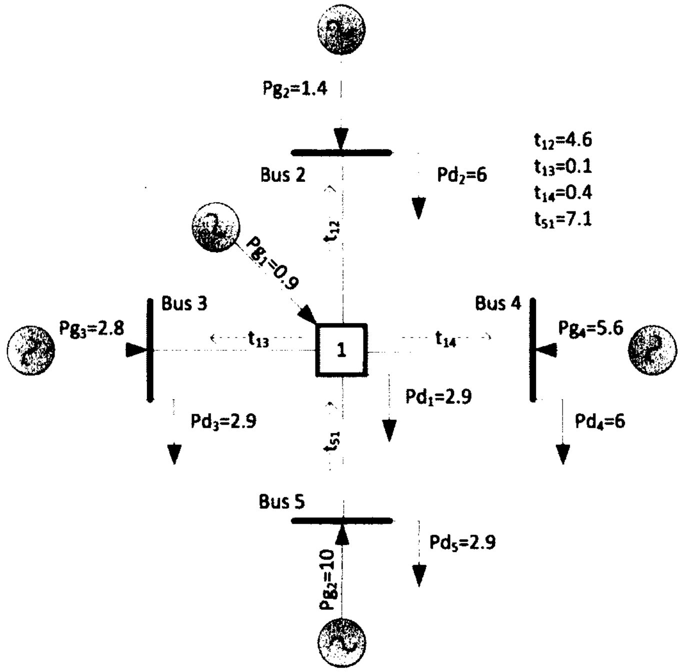

Figure 32: 5bus3tp Configuration

The first thing to notice is the fixed demand levels at Bus1 and Bus3. This change in demand from time period to time period needs to be offset with generation changing at the same rate. As a result of the energy constraint at Bus2 and Bus4 the energy constraints allows the demand to adjust during each time period while still meeting the constraint (Table 24). Additionally the demand preference allows for adjustment to minimize the global cost.

Table 21: 5b3Tp with/out fixed demand

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	12.304	0.9	2.9	0.972	6.822	-2.255	0
sb21	12.304	0.9	2.9	0.972	6.822	-2.255	0
sb31	12.304	0.9	2.9	0.972	6.822	-2.255	0
sb12	6.24	1.4	6	1.568	1.8	-2.255	-1.25
sb22	6.24	1.4	6	1.568	1.8	-2.255	-1.25
sb32	6.24	1.4	6	1.568	1.8	-2.255	-1.25
sb13	10.183	2.8	2.9	3.136	6.822	-2.255	0
sb23	10.183	2.8	2.9	3.136	6.822	-2.255	0
sb33	10.183	2.8	2.9	3.136	6.822	-2.255	0
sb14	1.474	5.6	6	6.272	1.8	-2.255	-1.25
sb24	1.474	5.6	6	6.272	1.8	-2.255	-1.25
sb34	1.474	5.6	6	6.272	1.8	-2.255	-1.25
sb15	0.813	10	2.9	10	6.822	-2.255	0
sb25	0.813	10	2.9	10	6.822	-2.255	0
sb35	0.813	10	2.9	10	6.822	-2.255	0

Global Minimum for the system is:	138.042

To put the effect of energy constraints and demand preferences into perspective we consider a 3 bus system over 24 time periods with a single generator at bus 2 and demand buses at 1 and 3. The following cases were considered:

- Case1: varying fixed demand every time period at buses 1 and 3
- Case2: varying fixed demand at Bus1 and a demand preference at Bus3
- Case3: varying fixed demand at Bus1 and a demand preference and energy constraint at Bus3

Table 22: 5b3Tp with fixed demand case 1

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	14.079	1.2	4	1.728	4.6	-2.7684	0
sb21	15.896	1.2	5	1.728	3	-2.9391	0
sb31	18.479	1.3	6	2.028	1.8	-3.1172	0
sb12	4.355	1.7	6.4	2.312	1.432	-2.768	-1.938
sb22	5.111	1.8	6	2.592	1.8	-2.939	-1.938
sb32	5.804	1.9	5.6	2.888	2.232	-3.117	-1.938
sb13	12.053	3.5	5	4.9	3	-2.768	0
sb23	14.036	3.7	6	5.476	1.8	-2.939	0
sb33	16.747	3.9	7	6.084	1	-3.117	0
sb14	-2.83	6.9	6.4	9.522	1.432	-2.768	-1.938
sb24	-2.988	7.3	6	10.658	1.8	-2.939	-1.938
sb34	-3.308	7.8	5.6	12.168	2.232	-3.117	-1.938
sb15	-3.182	10	1.6	10	10.072	-2.768	0
sb25	-4.656	10	1.2	10	11.208	-2.939	0
sb35	-6.272	10	0.7	10	12.718	-3.117	0

Global Minimum for the System is:	152.21

- Case 4: demand preferences and energy constraints at Bus1 and Bus3

In Figure 33 the generator output of Bus2 is plotted for each of the 24 time periods. It is clear that when both demands vary from time period to time period the generator must meet this varying demand. This is case 1 and similar to how instantaneous demand is met by utilities today. Case 2 introduces the first effect of a demand preference, which represents a customer that makes demand decisions based upon a preference associated between price and needs. This curve shows a reduction of variation of the generator output. This is seen by the smoothing of the output curve.

Case 3 brings the energy constraint into the picture and this reduces the variance even further. The energy constraint is equivalent to the same amount of energy in Case 1 at bus3. The variance can be equated to the second derivative the output curve, in other words, the rate of change of the rate of change. Adding the demand preference and finally the energy constraint reduces the changes in the second derivate. It is apparent that the output of the generator is constant over all the time periods in Case 4, which is producing the same amount of energy as Case 1. It should be noted that the smoothing effect has two factors, the demand preference function and the energy constraint. Adding demand preferences and energy constraints to the system both contribute to the smoothing of the generators outputs. As the number of demand preferences and energy constraints grow within the system the smoothing effect increases. Hence in the example presented with 2 demand buses the system immediately produced a constant output once both buses establish demand preferences.

In summary both the demand preferences and energy constraints contribute to driving the generators to constant outputs over the time periods considered. As the output of required generation no longer ramps, the problem of generation dispatch becomes a function of stacking generation at the most efficient operating point. It is important to understand what the contributing factors of demand preference and energy constraints are. Theorizing about potential mathematical functions that could represent a demand preference is abstract and difficult to understand. However approaching the problem from the other direction can provide a clearer view of how a demand preference function can be developed. This dissertation stated that there was no single concept, idea, implementation, experiment, or area of research that identifies the energy delivery paradigm; however it is the confluence of many factors that indicate a direction toward energy delivery The concept of a demand preference function and an energy constraint is a derivative of the evolution of electrical storage, TOU rates (Time Of Use) , real time pricing, demand response, electric vehicles, distributed generation, renewable integration, expanded monitoring and control, consumer preference in climate change, sustainability, and many others factors. These factors contribute to building of demand preferences in today's electrical delivery market. Aided by the advancement and integration of technology, communications, policy, markets, and societal factors consumers and producers are moving toward a definable preference function.

One example is the residential customer who purchases an electric vehicle. The owner has shifted from filling a fuel tank at a fuel station to charging at his home or other location. The desire to accomplish this at a lower price did not change and this becomes a preference of the electric demand associated with the electric vehicle. Hence the electric vehicle is contributing to the residential customers demand preference and potential energy constraints. The development of new technology like the electric vehicle has developed input to an electrical demand preference that was not their previously. The energy constraint of the electric vehicle is driven by the time and state of charge required by the owner. It is the different choices provided by the new technology that drive different electrical demand preferences and electrical energy constraints.

Similarly in a commercial or industrial setting, as TOU demand and energy rates along with demand response are introduced, commercial customers are developing electricity usage strategies to minimize or maximize business objectives, by examining usage and employing technology to meet objectives. This may include improving efficiency, deploying distributed generation, or further controlling demand. Ultimately commercial customers are developing emergent behaviors which can be described by demand preference functions

Therefore this dissertation sees the need to "leap frog" to energy delivery and focus on the factors and properties of the paradigm. .

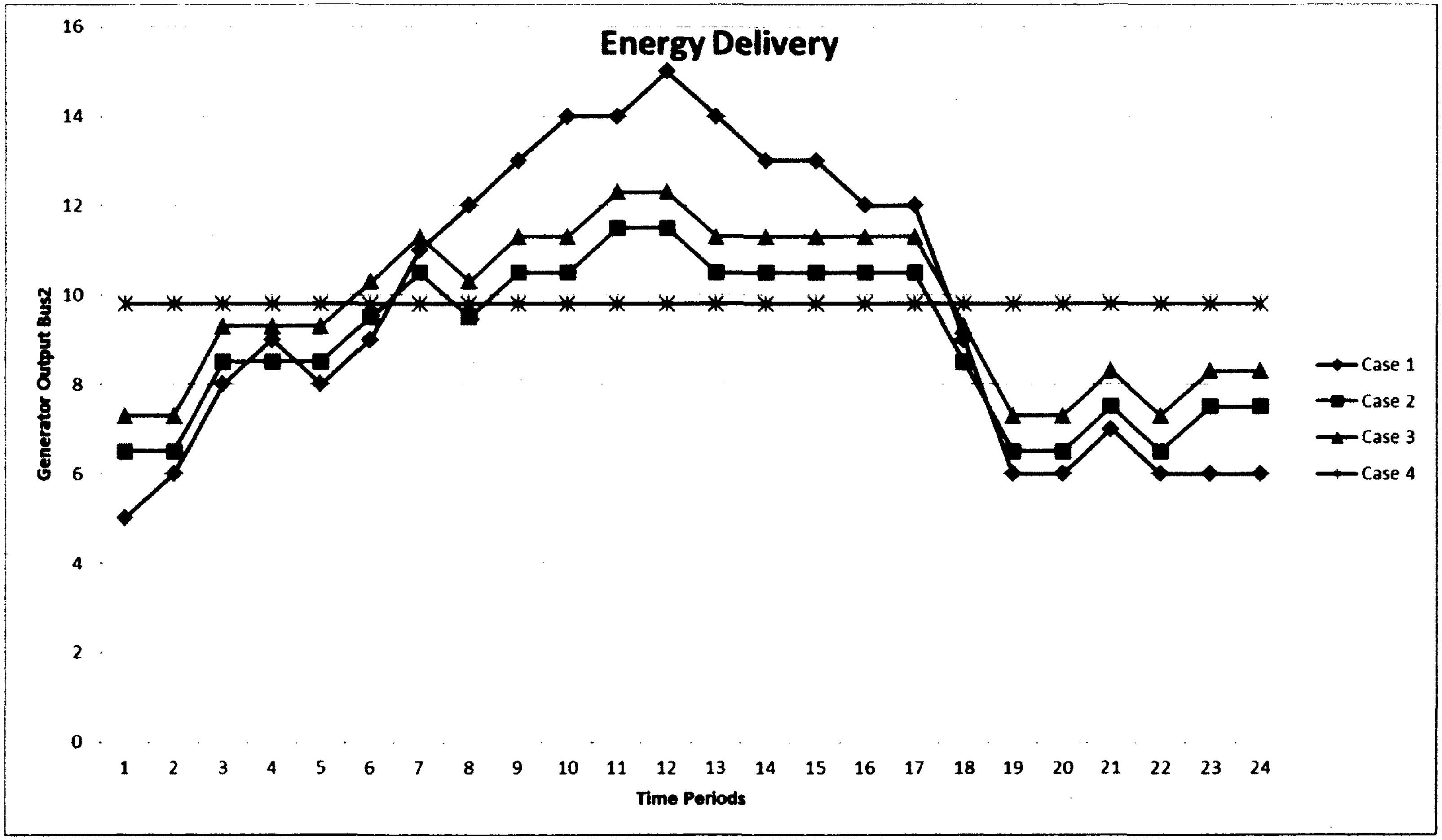

Figure 33: Energy Delivery Effect

THE CONFIGURATION EFFECT

One feature of how this algorithm was implemented is the ability to change a large amount of configuration information easily; and unforeseen benefits were the questions that arose from building the configuration interface which had not been thought about in the physical significance discussions. Several issues which had not been thought about nor discussed included:

- Should an agent be able to change its demand or generation preferences from time period to time period?
- Can a bus fix its demand or generation and how does this interact with a preference function and the formulation of the sub-problem algorithm?
- Is the energy constraint specified as a sum of estimates from time periods or can a bus have more than one energy constraint per configuration?
- Are there topologies that are not allowable?

Each question was addressed in the implementation of the algorithm and configuration interface. For example, demand preference and generation preferences were allowed to change between time periods; however is this practical in actual implementation? It seems more intuitive that a shift in demand/generation preference would take place between different bidding events where the network ran the algorithm. It is very possible to allow the shift in preferences; however it is directly tied to the Lagrangian multipliers within the system. This is represented in the 3b2tp results below, where demand preferences are kept constant and generation preferences are allowed to change between time periods. In this example, there are 2 operating points, one for time period one and another for time period two, which is supported by the different transmission line Lagrangian multipliers, $\lambda_1 = -1.531$ and $\lambda_2 = -2.653$ (Table 25).

Table 23: 2b2tp different gpref

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	3.994	3.8	4	2.888	0.8	-1.531	0
sb21	6.657	3.2	3.4	4.096	2.048	-2.563	0
sb12	3.408	4.6	4	3.527	0.8		0
sb22	5.836	3.8	3.4	4.813	2.048		0
sb13	3.994	3.8	4	2.888	0.8		0
sb23	6.657	3.2	3.4	4.096	2.048		0

Global Minimum for the System:	30.852

As we add an energy constraint to each bus, $E_i = 8$, the same effect of two operations points is present in the results (Table 26). The changing of preferences during the algorithm has similar results to managing instantaneous power demands.

Table 24: 2b2Tp different gpref and E

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	mu
sb11	1.925	4	4.3	3.2	0.392	-1.609	-0.5
sb21	4.936	3.4	3.6	4.624	1.568	-2.719	-0.5
sb12	1.277	4.8	4.3	3.84	0.392		-0.5
sb22	4.012	4.1	3.6	5.603	1.568		-0.5
sb13	1.925	4	4.3	3.2	0.392		-0.5
sb23	4.936	3.4	3.6	4.624	1.568		-0.5

Global Minimum for the System:	30.971

The question of fixed demand or generation was addressed so that a specific amount of demand or generation could be configured in each time period if required. Additionally the energy constraint was implemented so each convergence of the algorithm represented a single energy constraint over all time periods considered. However the last question of topology was originally limited to ranges of topologies from star to radial and did not allow loops, however the algorithm was adapted to handle loops. The ability to handle loops within the algorithm was centered on determining the transmission line constraints of multi-transmission line node without the initial value from single transmission line nodes.

In the next configuration we see an 8b2tp system, Figure 34, where demand is only located in the inner loop (buses 1-4) and generation is attached at each vertex outside the loop (buses 5-8).

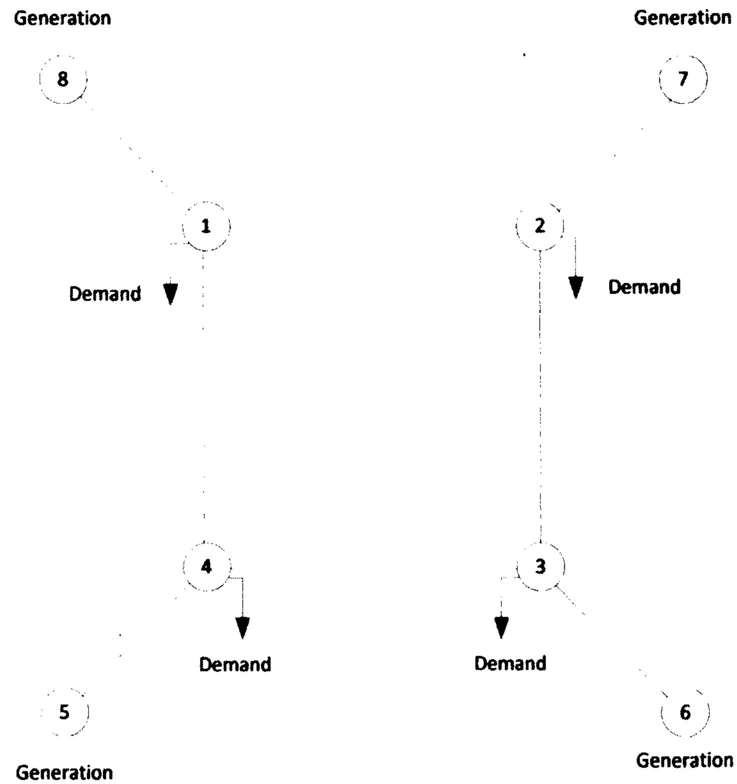

Figure 34: Loop Example

Again starting with a simple case, all generators preferences (bus 5-8) are equivalent and demand preferences (bus 1-4) are equivalent. The result in Table 27 show power is delivered from every corner generator to the closest to vertex. This does not demonstrate the loop delivering power, however it validates an important concept that the algorithm effectively deals with the multi transmission line situation in a loop. Next the generation preference is reduced by a factor of 2 at bus 8. The expected results of having generator 8 increase its output is reflected in the results in Table 28.

The results for a more complicated problem are shown in Table 29, where demand preferences are varied, energy constraints added, fixed demand configured, and generation preferences are changed. (Bus 1 has fixed demand of 3, bus 2 and bus 4 had energy constraints). One important note is that the generation preference of bus 5 was set higher than all other generators and thus it did not have an output.

Table 25: Loop 1 results

subproblem	sbmin	Pg	Pd	gCost	dCost	cp
sb11	7.3	0	4	0	0.8	-1.625
sb21	7.3	0	4	0	0.8	-1.625
sb12	7.3	0	4	0	0.8	-1.625
sb22	7.3	0	4	0	0.8	-1.625
sb13	7.3	0	4	0	0.8	-1.625
sb23	7.3	0	4	0	0.8	-1.625
sb14	7.3	0	4	0	0.8	-1.625
sb24	7.3	0	4	0	0.8	-1.625
sb15	-3.301	4.1	0	3.362	0	-1.625
sb25	-3.301	4.1	0	3.362	0	-1.625
sb16	-3.301	4.1	0	3.362	0	-1.625
sb26	-3.301	4.1	0	3.362	0	-1.625
sb17	-3.301	4.1	0	3.362	0	-1.625
sb27	-3.301	4.1	0	3.362	0	-1.625
sb18	-3.301	4.1	0	3.362	0	-1.625
sb28	-3.301	4.1	0	3.362	0	-1.625

Table 26: Loop 2 results

subproblem	sbmin	Pg	Pd	gCost	dCost	cp
sb11	5.974	0	4.2	0	0.512	-1.313
sb21	5.974	0	4.2	0	0.512	-1.313
sb12	6.076	0	4.2	0	0.512	-1.313
sb22	6.076	0	4.2	0	0.512	-1.313
sb13	6.025	0	4.2	0	0.512	-1.313
sb23	6.025	0	4.2	0	0.512	-1.313
sb14	6.024	0	4.2	0	0.512	-1.313
sb24	6.024	0	4.2	0	0.512	-1.313
sb15	-2.153	3.3	0	2.178	0	-1.313
sb25	-2.153	3.3	0	2.178	0	-1.313
sb16	-2.153	3.3	0	2.178	0	-1.313
sb26	-2.153	3.3	0	2.178	0	-1.313
sb17	-2.153	3.3	0	2.178	0	-1.313
sb27	-2.153	3.3	0	2.178	0	-1.313
sb18	-4.307	6.6	0	4.356	0	-1.313
sb28	-4.307	6.6	0	4.356	0	-1.313

Table 27: Loop 3 results

subproblem	sbmin	Pg	Pd	gCost	dCost	cp
sb11	262.737	0	3	0	3.2	-1.3125
sb21	262.737	0	3	0	3.2	-1.3125
sb12	8.129	0	4.1	0	0.648	89.875
sb22	8.129	0	4.1	0	0.648	89.875
sb13	-76.735	0	5	0	1	23.625
sb23	-76.735	0	5	0	1	23.625
sb14	-1.088	0	4.5	0	0.6	-1.5313
sb24	-1.088	0	4.5	0	0.6	-1.5313
sb15	0	0	0	0	0	-2.1875
sb25	0	0	0	0	0	-2.1875
sb16	-1.465	1.9	0	1.444	0	89.875
sb26	-1.465	1.9	0	1.444	0	89.875
sb17	-5.938	5	0	5	0	-1.5313
sb27	-5.938	5	0	5	0	-1.5313
sb18	-11.875	10	0	10	0	89.875
sb28	-11.875	10	0	10	0	89.875

IEEE 13 BUS SYSTEM

The examples in this dissertation make up less than 1% of the total configurations run and examined, however they demonstrate key aspects of the algorithm and methodology of implementation. Applying the implemented algorithm to an accepted test configuration provides an opportunity to demonstrate an adequate sanity check. To complete this aspect, an IEEE 13 Bus system was slightly altered which included replacing transformers and voltage compensators with buses. The actual impedances of the lines were implemented into the configuration and bus names were renamed from 1-13 instead of the 600 series in the IEEE specification. Below is the adapted IEEE 13 Bus system. Several different configurations were built and run against the IEEE 13 bus system to demonstrate different aspects of generation, demand, and energy constraints. It was decided that a "utility" model for a customer driven microgrid would be presented in normal and islanded mode. In this configuration bus 1 acts as a large generation agent with no demand, the utility. Buses 2-13 were a mixture of fixed demand, demand preferences, and energy constraints representing diversity on the distribution feeder. Additionally buses 2,5,8,10,13 have some local generation. Total local demand did not exceed the utility capacity of the utility which had the lowest generation function with all other generation being equal. This represents a plausible configuration of the customer driven microgrid.

- Bus1: Utility generation only

- Distributed generation at bus: 2, 4, 8, 10, and 13
- Demand preference functions vary between buses 2-13
- Energy Constraints at bus: 3 and 9

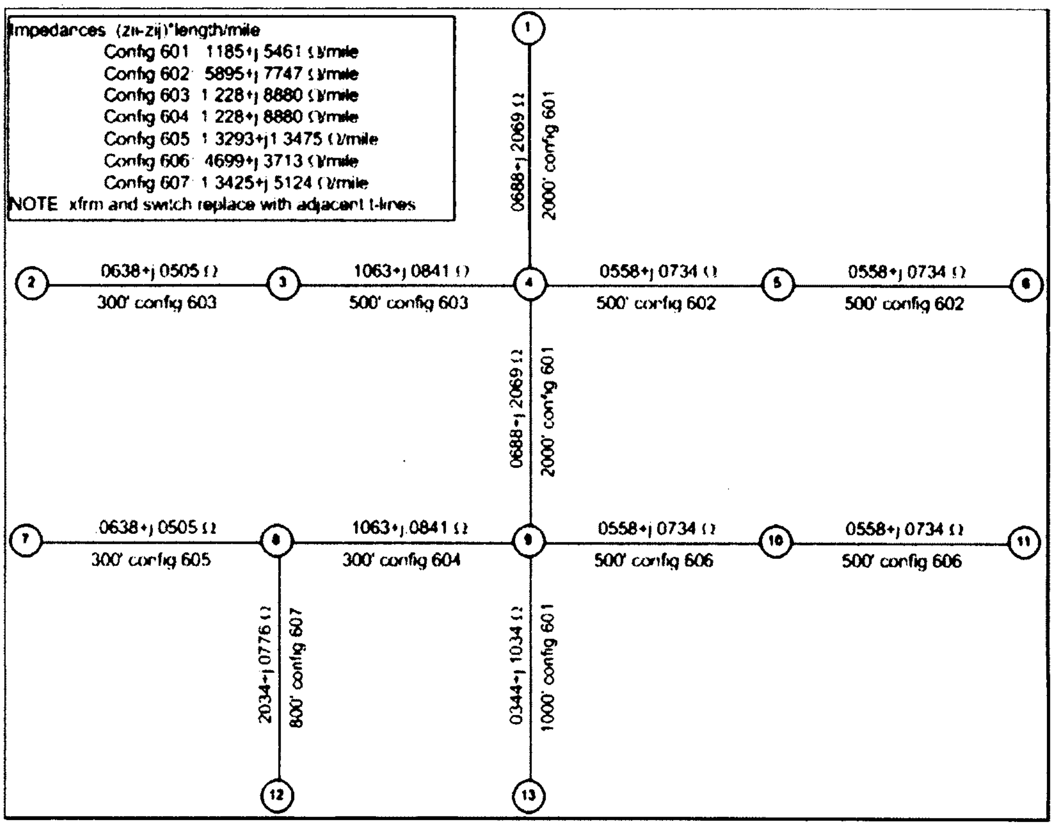

Figure 35: Adapted IEEE 13 Bus System

Several different configuration where examined to demonstrate the effect of different preference functions and the corresponding contribution. Convergence of the algorithm was significantly helped with utilization of the convexing term added to the sub-problem.

The 13 Bus system exhibited properties consistent with smaller examples. Generation with a lower cost was utilized more than higher cost generation. Similarly demand with higher cost was served less than demand with lower cost. Additionally demand preference functions and energy constraints help push generation output toward a constant value for each generator for all time periods. Without a fixed demand in the system, the demand at buses with energy constraints was constant over every time period. As the fixed demand values were implemented per time period (not equal every time period) demand at the energy constraints buses varied based upon the implementation of fixed demand at different time periods. This is consistent with algorithm meeting time period constraints with instantaneous power requirements. In other words, as demand values were fixed to different values the buses with energy constraints experienced a change in demand per time period essentially absorbing the change in demand from the fixed demand buses. This "absorbing" of change in demand is also demonstrated by the inherent function of demand preference functions, where solving for the global minimum will drive the energy cost up as the fixed demand enter the picture. The result is the demand preference function backs off. This represents a key function of a prosumer interaction within this algorithm and implementation with Lagrangian Relaxation, energy constraint, and demand preference. Table 30 represents the demand at Bus5 fixed at the values shown in each time period, and as a result the only generator, the utility, must adjust to the demand, however not at the same scale due to the demand preferences at other buses adjusting slightly. In other words, a step in demand at Bus4 is compensated for by both the utility and other customers within the microgrid with demand preference functions (Table 30). In this example Bus7 responds to the generation cost and adds more demand when Bus4 demand goes to zero.

Table 28: Generation adjusting

Case 1: No Energy Constraint

	subproblem	sbmin	Pg	Pd	gCost	dCost
Bus 4	sb15	-0.315	0	4	0	3.673
	sb24	20.015	0	0	0	20
	sb35	-0.315	0	4	0	3.673
Utility	sb11	-14.059	37.5	0	14.063	0
	sb21	-12.347	35.2	0	12.39	0
	sb31	-14.059	37.5	0	14.063	0
Bus 7	sb17	6.836	0	3.9	0	1.961
	sb27	0.816	0	5	0	0.816
	sb37	6.836	0	3.9	0	1.961

Furthering this example we add an energy constraint to bus 6 and see how in addition to the demand preference of bus 7 responding, the energy constraint responds and allows the algorithm to find a minimum where the generation to a constant output. Note in Table 30, the generation during time period 2 is 35.2 kWh versus the 35.5 kWh in timer periods 1 and 3. This is showing the error in the algorithm of -0.3kWh which can be subtracted from generation during bus 2 to get the same value of 35.5kWh of output. Tuning the algorithm results in smaller and smaller error, but ultimately determined by architectural decisions within the algorithm (Table 31).

Table 29: Energy constraint addition

Case 2: 2 Energy Constraints

	subproblem	sbmin	Pg	Pd	gCost	dCost
Bus 4	sb15	8.679	0	4	0	3.673
	sb24	20.015	0	0	0	20
	sb35	8.679	0	4	0	3.673
Utility	sb11	-14.059	35.5	0	14.063	0
	sb21	-12.347	35.2	0	12.39	0
	sb31	-14.059	35.5	0	14.063	0
Bus 6	sb16	12.281	0	2.6	0	5.131
	sb26	9.103	0	3.8	0	2.437
	sb36	12.281	0	2.6	0	5.131
Bus 7	sb17	8.964	0	2.3	0	4.508
	sb27	4.566	0	5	0	0.816
	sb37	8.964	0	2.3	0	4.508

In addition to the utility being the largest generation on the customer driven microgrid, an islanding scenario was also run. Under this scenario the utility generation was forced to zero and the remaining buses with demand and generation preference function operated the microgrid. In this configuration generation was at buses 3, 4,8,10, and 13 in smaller scale and higher cost preference and the demand preferences, fixed demand, and energy constraints remained the same. The results in Table 32 show the same smoothing effect to varying demand at Bus5 by the preference functions and the energy constraints at the other buses. It should be noted that the buses closer to the step demand at Bus5 provided more adjustment than demand and generation further from Bus5.

Table 30: IEEE 13 Bus Islanded

Case 3: Isanded versus grid connected

		Grid Connected			Islanded		
	subproblem	sbmin	Pg	Pd	sbmin	Pg	Pd
Bus 1	sb11	35.5	0	12.602	0	0	0
	sb21	35.2	0	12.39	0	0	0
	sb31	35.5	0	12.602	0	0	0
Bus 2	sb12	0	4.9	0	11.062	0	4.4
	sb22	0	4.9	0	8.531	0	5.7
	sb32	0	4.9	0	11.062	0	4.4
Bus 3	sb13	0	4.8	0	0.059	7.9	3
	sb23	0	4.3	0	-1.871	8.4	2.9
	sb33	0	4.8	0	0.059	7.9	3
Bus 4	sb14	0	0	0	15.046	6.4	0.5
	sb24	0	0	0	8.255	4.8	2.7
	sb34	0	0	0	15.046	6.4	0.5
Bus 5	sb15	0	4	0	4.281	0	4
	sb25	0	0	0	20.1	0	0
	sb35	0	4	0	4.281	0	4
Bus 6	sb16	0	2.6	0	13.031	0	3.2
	sb26	0	3.8	0	13.732	0	2.6
	sb36	0	2.6	0	13.031	0	3.2
Bus 7	sb17	0	2.3	0	1.441	0	5
	sb27	0	5	0	2.691	0	5
	sb37	0	2.3	0	1.441	0	5
Bus 8	sb18	0	10	0	11.87	17.7	10
	sb28	0	10	0	11.558	17.6	10
	sb38	0	10	0	11.87	17.7	10
Bus 9	sb19	0	0	0	3.802	0	6.4
	sb29	0	0	0	3.823	0	6.5
	sb39	0	0	0	3.802	0	6.4
Bus 10	sb110	0	0	0	7.994	6.2	2.2
	sb210	0	0	0	8.031	6.2	2.1
	sb310	0	0	0	7.994	6.2	2.2
Bus 11	sb111	0	2	0	11.566	0	4.6
	sb211	0	2	0	11.589	0	4.6
	sb311	0	2	0	11.566	0	4.6
Bus 12	sb112	0	2	0	10	0	3.5
	sb212	0	2	0	10	0	3.5
	sb312	0	2	0	10	0	3.5
Bus 13	sb113	0	2	0	-8.898	10	2
	sb213	0	2	0	-8.898	10	2
	sb313	0	2	0	-8.898	10	2
Global Minimum:			283.387			362.387	

CAPACITY LIMITS ON A TRANSMISSION LINE

One concept that was investigated in this microgrid operation algorithm was the limiting of power over specific transmission lines within the topology of each system. This concept is significant in any power flow and as local microgrids form interconnections between other microgrids power flow limits are more significant. To implement this concept, the original formulation was reformulated with the new constraints.

Consider minimizing the cost function: $f^T(P_{g_i}, P_{d_i}) = \sum_{i=1}^{m} G^T{}_{CP_i}(P_{g_i}) + \sum_{i=1}^{m} D^T{}_{CP_i}(P_{d_i})$

Subject to:

$$\begin{aligned} &P_{g_i} - P_{d_i} - t_{ij} = 0 \\ &t_{ij} + t_{ji} = 0 \\ &-C_{i\max} \le t_{ij} \le C_{i\max} \\ &-C_{i\max} \le t_{ji} \le C_{i\max} \end{aligned}$$

where the new constraints are $-C_{i\max} \le t_{ij} \le C_{i\max}$ and $-C_{i\max} \le t_{ji} \le C_{i\max}$.

These constraints represent limits to the amount of power that can flow in a transmission line. Developing the new Lagrangian for the cost function from Figure 36:

$$L = L_{old} + \sum_{m=1}^{ntp} \sum_{j=1}^{ntlines} t_{cap_{dir}} \gamma_j^m (t_j^m - C_j^m)$$, where

L_{old} = the Lagrangian from the previous formulation

γ_j^m = the new Lagrangian multipliers for each transmission line limit

$t_{cap_{dir}}$ = represents the needed direction for the new Lagrangian (+/-)

t_j^m = the amount of power flowing in the transmission associated with γ

C_j^m = the constraint value of the transmission line

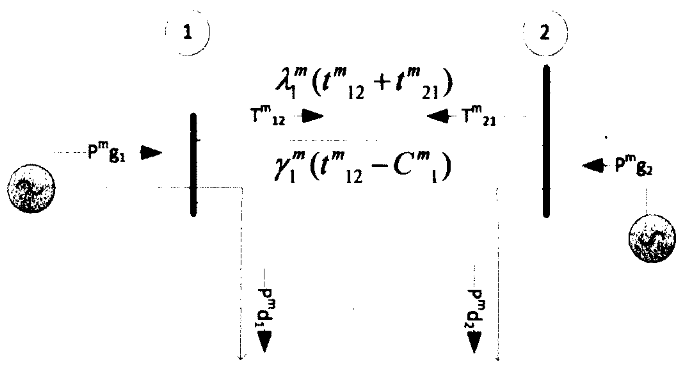

Figure 36: 2b2tp with Transmission Line Limits

Examining this for a 2bus2tp system without energy constraints becomes:

$L = M + \lambda_1^1(t^1{}_{12} + t^1{}_{21}) + t_{cap_{dir}} \gamma_1^1 (t^1{}_{12} - C^1{}_1) + \lambda_1^2(t^2{}_{12} + t^2{}_{21}) + t_{cap_{dir}} \gamma_1^2 (t^2{}_{12} - C^2{}_1)$. The new Lagrangian has an extra term representing the transmission line limit constraint. In the formulation there are ntlines (# of t-lines) x ntp (# of time periods) new

Lagrangians. These directly affect the sub-problems by adding an additional term with the new Lagrangian multiplier, γ .

$$\text{sbpr 11: minimize } G^1_{CP_1} + D^1_{CP_1} + \lambda^1_1(Pg^1_1 - Pd^1_1) + t_{cap_{dir}}\gamma^1_1(t^1_{12})$$

$$\text{sbpr 21: minimize } G^2_{CP_1} + D^2_{CP_1} + \lambda^2_1(Pg^2_1 - Pd^2_1) + t_{cap_{dir}}\gamma^2_1(t^2_{12})$$

$$\text{sbpr 12: minimize } G^1_{CP_2} + D^1_{CP_2} + \lambda^1_1(Pg^1_2 - Pd^1_2) + t_{cap_{dir}}\gamma^1_1(t^1_{21})$$

$$\text{sbpr 22: minimize } G^2_{CP_2} + D^2_{CP_2} + \lambda^2_1(Pg^2_2 - Pd^2_2) + t_{cap_{dir}}\gamma^2_1(t^2_{21})$$

It should be noticed that $t^k_{ij} = Pg^k_i - Pd^k_i$ for a bus with a single transmission line and for a bus with multiple transmission lines t^k_{ij} must be calculated in the same method employed for determining flow previously mentions. Hence once the transmission line constraints of $t_{ij} + t_{ji} = 0$ have been met, the algorithm will verify the transmission line capacity constraints. It should be recognized that if the transmission line constraint is met, and the capacity of the line is above the constraint, the algorithm will find two violations for TL_k (transmission line k). The violation will be for $t_{ij} - C_k > 0$ and $t_{ji} + C_k < 0$. Given the two violations the Lagrangian multiplier γ_k must be increased for bus_i and decreased for bus_j.

For the first example a 2b2tp system is configured with generation at bus 1 and demand at bus 2 with a limit of 25 for the transmission line limit, far above the generation and demand capacity. The results show that level of 6.5 kW flow each period (Table 33).

Table 31: 2b2tp Capacity 25

Transmiss Line	Constraint have	converged!!!!!		
T-Line 21:00 -->	t12=6.50	t21=-6.50 with	constraint dv21/cp21=0.00000/-0.79688	
Pg11 = 6.5	Pd11 = 0	Pg12 = 0	Pd12 = 6.5	sbmin = 6.53
Pg21 = 6.5	Pd21 = 0	Pg22 = 0	Pd22 = 6.5	sbmin = 6.53

If we now adjust the capacity limit of TL_1 to 5kW limit, where $C_1 = 5\,\text{kW}$ we see that the capacity Lagrangian has increased to 0.3 for the sub-problem, Table 34. Based upon the conditions of the test for the constraint, the algorithm found that Bus1's capacity Lagrangian multiplier was increased and Bus2's capacity Lagrangian multiplier was decreased. Another good example of the capacity constraint in the algorithm is provided in a 3b3tp loop as seen next in Figure 37.

Table 32: 2b2tp Capacity 5

Transmiss Line	Constraint have	converged!!!!!	qv21/cq=0.200/-.300	
T-Line 21:00 -->	t12=4.80	t21=-4.80 with	constraint dv21/cp21=0.00000/-0.9690	
Pg11 = 4.8	Pd11 = 0	Pg12 = 0	Pd12 = 4.8	sbmin = 10.338
Pg21 = 4.8	Pd21 = 0	Pg22 = 0	Pd22 = 4.8	sbmin = 10.338

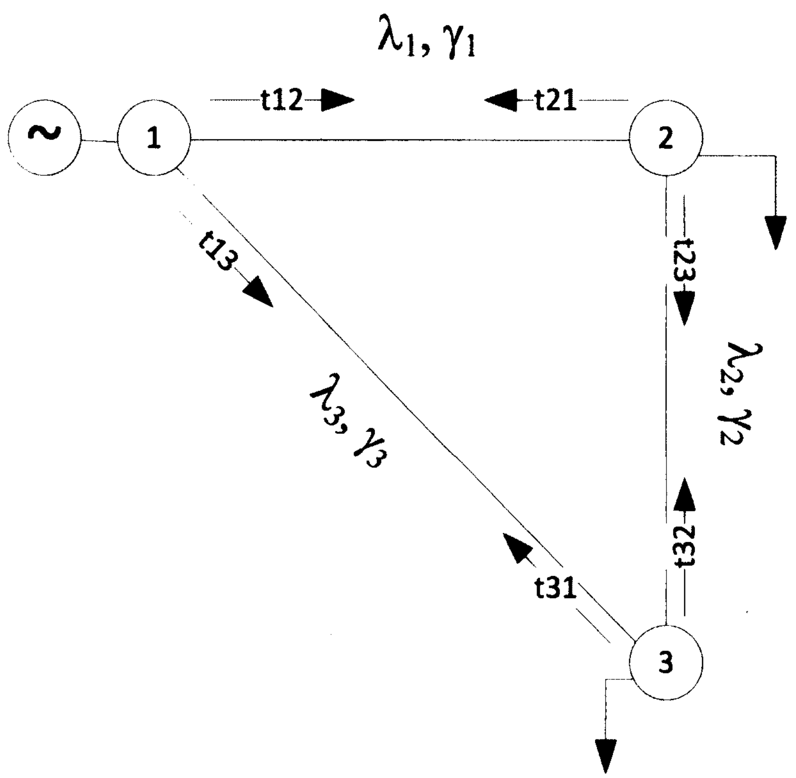

Figure 37: 3b3tp Loop Configuration

Bus 1 is configured with generation and bus2 and bus3 have different demand preferences with an energy constraint of 15 at bus2. The initial results show that bus1 generates at a rate of 15kW and 6.67 kW flow via t_{12} and 8.33 via t_{13}, and finally 1.67 flow via t_{23} resulting in a demand rate of 10kW at bus 2 and 5 kW at bus 1 (Table 35). If a capacity constraint of 5 kW is set on t_{12} the results show that flow reduced to 5 kW, with a flow increase to10kW via t_{13} and an increase to 5kW via t_{23} and the energy constraint is still met at bus 2 (Table 36). Essentially the network has adapted to the capacity constraint and still meets the energy requirements of the system.

Table 33: 3b2TP Z23=Z13=Z12 no capacity constraint

T-Line	31:00:00	-->	t12=6.65	t21=-6.67
T-Line	32:00:00	-->	t13=8.35	t31=-8.34
T-Line	33:00:00	-->	t23=1.67	t32=-1.66

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	mu	cq
sb11	-0.698	15	0	1.125	0	-0.4063	0	0
sb21	-0.698	15	0	1.125	0	-0.4063	0	0
sb31	-0.698	15	0	1.125	0	-0.4063	0	0
sb12	17.106	0	5	0	5	0.1055	1.844	0
sb22	17.106	0	5	0	5	0.1055	1.844	0
sb32	17.106	0	5	0	5	0.1055	1.844	0
sb13	0.945	0	10	0	2	0.1055	0	0
sb23	0.945	0	10	0	2	0.1055	0	0
sb33	0.945	0	10	0	2	0.1055	0	0

One important distinction of the new capacity Lagrangian multipliers γ_k is that the constraint is an inequality versus the equality provided by λ_k, the transmission line Lagrangian multiplier. This difference in constraint type changes the how the search is accomplished. The search for λ_k is accomplished with a steepest descent, where a specific value allows the equality constraint to be met. Conversely the search for γ_k is accomplished by searching for the smallest value which can make the inequality satisfied. Thus there are many values of γ_k that can satisfy the inequality.

Table 34: 3b2TP Z23=Z13=Z12 with capacity constraint

T-Line	31:00:00	-->	t12=4.99	t21=-5.00
T-Line	32:00:00	-->	t13=10.01	t31=-10.00
T-Line	33:00:00	-->	t23=0.00	t32=0.00

subproblem	sbmin	Pg	Pd	gCost	dCost	cp	cq	mu
sb11	-1.109	15	0	1.125	0	-0.8164	0.03	0
sb21	-1.109	15	0	1.125	0	-0.8164	0.03	0
sb31	-1.109	15	0	1.125	0	-0.8164	0.03	0
sb12	18.455	0	5	0	5	0.1836	0.03	1.844
sb22	18.455	0	5	0	5	0.1836	0.03	1.844
sb32	18.455	0	5	0	5	0.1836	0.03	1.844
sb13	0.164	0	10	0	2	0.1836	0.03	0
sb23	0.164	0	10	0	2	0.1836	0.03	0
sb33	0.164	0	10	0	2	0.1836	0.03	0

SUMMARY DISCUSSION

It can be seen that the Lagrangian Relaxation is a dynamic technique for global optimization with equalities and inequalities. The Lagrangian Relaxation provides a valuable characteristic in developing sub-problems that solved independently of non-neighboring buses, thus allowing for implementation of a distributed or centralized scheme to determine solutions, which illuminates the minimal requirements of communications via the 'DC power flow' and the Lagrangian multiplier. This implementation provides an in depth look at Lagrangian Relaxation for the operation of a microgrid via a global minimization function. Constraints are introduced that represent typical power flow parameters as well as constraints that support the concepts behind an energy delivery paradigm. The benefits of the energy paradigm are demonstrated to show strong smoothing of generator output levels for any type of system or configuration. This is supported by the reduction in cost per unit of energy as energy constraints are introduced by agents. This concept is critical to understanding important characteristics and advantages of the energy paradigm. By shifting the responsibility of instantaneous power to the consumer, producers are able to deliver energy to a customer essentially changing the underlying market and enabling new markets. As seen in Figure 31, the energy deliver paradigm allows the output of the generator to move toward a constant output depending on the number of buses participating in demand preferences and energy constraints. Applying the market clearing to the same system represented in Figure 31 shows the reduction in cost per unit of energy. The results are shown in Figure 38, where the cost per unit energy varies between $0.25 and $.0125 with an average of $0.198 per unit under the varying demand versus a unit cost of $0.1875 for the same amount of energy with energy constraints.

The author does not believe this is an overnight change, but something on the horizon as more and more embedded systems become integrated to everyday lives, providing us with additional information and control. [34] Additionally as the electric industry begins to look closer at its capacity requirements growing year over year, it is believe that this will provide additional pressures to change the way electrical energy is used and delivered.

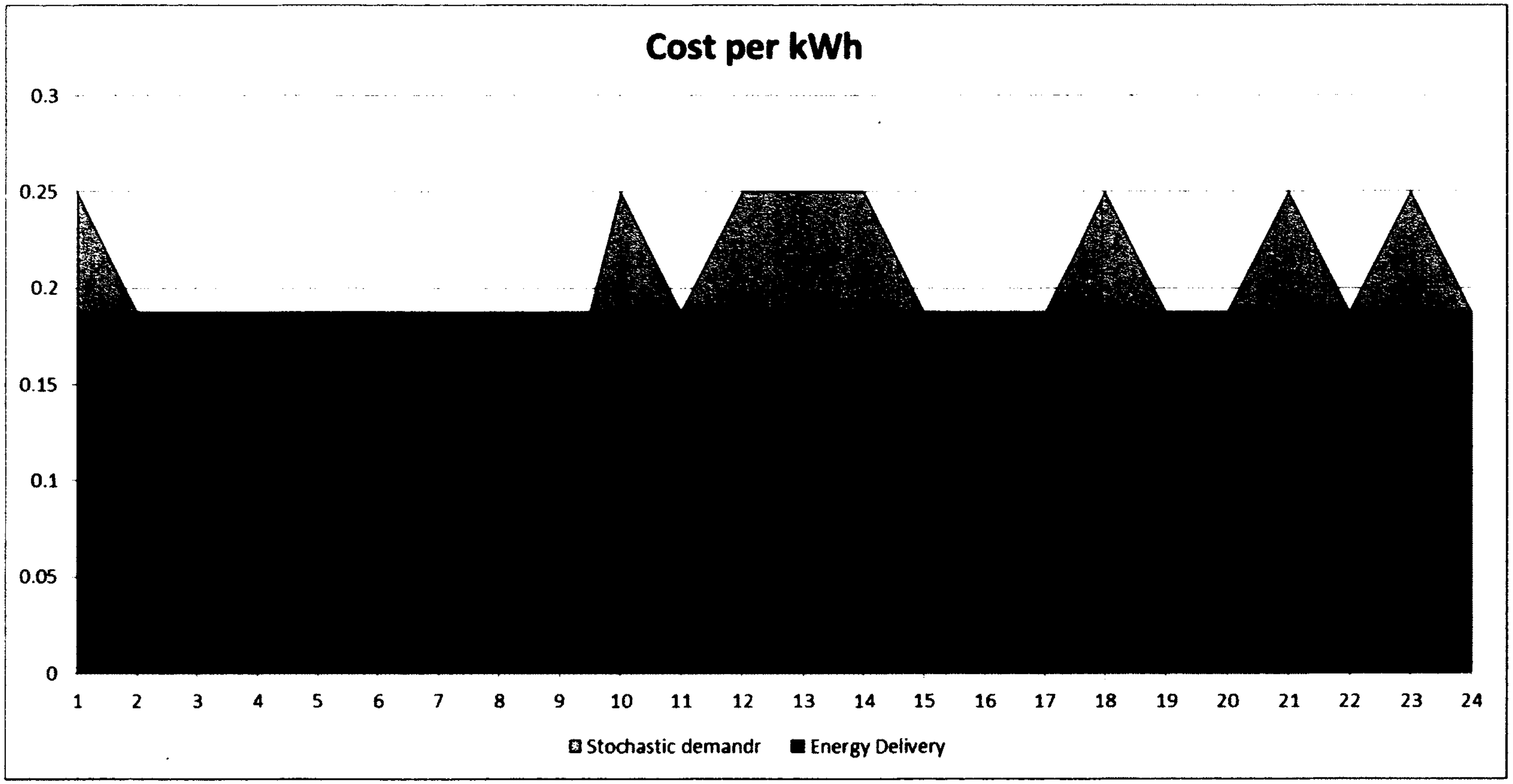

Figure 38: Cost per kWh

REMARKS

As the additional constraint of capacity is added to the system, the number of control variables and parameters has grown significantly within the configuration and algorithm itself. Hence it is very easy to build a configuration that does not have a viable solution, for example the transmission line constraints and capacities may be met, however the energy constraint which operates over all constraints may force the sub-problem to increase or decrease based upon the needs of the energy constraint. This action may cause the capacity constraints to fail and have the algorithm push against itself. In other words the energy constraint is requiring more power during a time period, however this violates the capacity constraint and the algorithm will bounce against itself trying to meet a constraint that may violate another. Similar misconfiguration can be seen when increasing the number of time periods as there are several parameters that must have time period dependent values.

It is important to note as discussed earlier, this algorithm is essentially a power flow in disguise and that the configuration parameters require the impedances of the transmission lines to be able to guess a power level at an adjacent bus in what is called the delta function within the algorithm. This is similar to a Guass-Seidel power flow where the voltage is guessed at adjacent nodes. Hence with the impedance information of the system, the algorithm can also adjust flow by adjusting the impedances of the lines.

One of the powerful tools applied to this algorithm was the adaption of configuration worksheets. This allowed many different adaptations to be demonstrated by changing input configuration. However the most benefit was the concepts introduced by the decision process of making configuration parameters available. Specifically minimum and maximum values on demand, which allowed for configuration of fixed values, change of demand and generation preferences over different time periods, and ingestion of different demand preferences from simple polynomials to fuel rates of internal combustion engines with cost of fuel.

APPENDICES

APPENDIX A

DETAILS OF "TIGHTENING" AND "LOOSENING" CONSTRAINTS WITHIN ALGORITHM

Within the algorithm the primary areas for the tuning parameters are associated with changing the Lagrangian multiplier size and the overall exit for each constraint associated with the Lagrangian multipliers. In the algorithm 2 types of Lagrangian multipliers are discussed: transmission line Lagrangian multipliers and energy Lagrangian multipliers. Both of these are associated with the same tuning, but with separate parameters, meaning they are not both controlled with the same parameters.

This first tuning parameter is associated with the decision to change the Lagrangian multiplier. This asks is the transmission line constraint or the energy constraint close enough to the set error? If it is don't change the value of the Lagrangian multiplier. If it is NOT close enough, then change the value of the Lagrangian multiplier. Overall the convergence of the system is then dependent upon the overall system error with is an average of each type of constraint error with a weight. Given this multi-stage tuning parameters it is possible to develop a configuration that cannot converge, however slight adjustments in tuning terms provides for convergence. For example, the constraint error on the transmission line needs to be related to the quantizing size of the generation and demand as well as a reasonable percentage of the largest generation. If for example the step size of the generation or demand was .1 and the error for the system error of .15, it is very possible to not converge. It is possible to see that a very tight constraint on the overall system may not be met if the quantizing size of the generation and demand is in relative magnitude. This phenomena can happen at the transmission line or energy constraint level and needs adjusted as the topology, fixed demand, and capacity changes within the system configuration. Below is a list of parameters from the code which are important to tuning:

cxi- the coefficient of the 'convexing' term

cpstsz_reduction - value of steepest decent reduction for transmission

cplimit – value of constraint must below to not adjust transmission line Lagrangian multipier associated with a percentage of largest demand and generation

cp11- if vale of cpstsz becomes below this value try again

exit_toosmall – system has iterated to many times, most likely bouncing

mustsz_reduction – value of steepest decent reduction for energy

tcev – constraint limit for transmission line constraints

evfct – weight used in determining evboundavg with evbound

evbound – percentage of the energy constraint used relating to evboundavg

APPENDIX B

CONFIGURATION SPREADSHEETS DETAILS

Upon the final writing and updating of the Matlab code for the Energy Delivery Paradigm a total of 4 spreadsheets comprised of 22 different worksheets made up the configuration data for a system. It is important to break down the configuration files to understand the configuration requirements of the system.

TOPOLOGY.XLSX

To begin the process a topology of the system to be analyzed is established. This topology must be consistent throughout all 4 spreadsheets. For an initial starting point the spreadsheet "Topology.xlsx" needs to be built. The Topology.xlsx spreadsheet is made up of 3 worksheets: <Lines>, ,<Tlines>, and <ancillary>.

<Lines> worksheet is a matrix of buses identifying the interconnection of the buses in the system consisting of 3 values. For any value on the diagonal of the matrix represents the max generation capacity of the generator located on the bus. For any off-diagonal cell (i,j), the value is either a 1 or a 0 with a 1 meaning there is a transmission line between the bus_i and bus_j. If there is no transmission line between the two buses then a value of 0-is configured.

<Tlines>, is an identical worksheet as : <Lines>, and represents the capacity limits of the transmission lines identified, however there is no value in the diagonal,

and values in the off –diagonal represent the capacity limits of the transmission line. If there is not a limit simply setting the value to a large number is sufficient.

<ancillary>, in the Topology.xlsx spreadsheet represents characteristic of the generators of the system. In this worksheet each buses generation capacity, stepsize of generator, sprint capacity, as well as fuel cost. Hence the worksheet is a list of buses for the system with capacity of each generator as well as

SERIESIMPEDANCE.XLSX

The "SeriesImpedance.xlsx" spreadsheet has one worksheet which contains transmission line impedance information for the corresponding topology contained in the "Topology.xlsx" spreadsheet.

<Series Impedance> - this worksheet has impedance values of each transmission line in the system.

GENERATIONPREFERENCES.XLSX

The "GenerationPreference.xlxs" spreadsheet has 9 worksheets within it of which 4 provide direct configuration information to the MatLab algorithm.

<Type> this worksheet enables input of generator fuel consumption curves from data contained in <Normalized>, <control>, and <Varying> worksheets or the use of direct entry of polynomial which is related to <gpoly> and <work> spreadsheets.

<pref> worksheet describes the polynomial or generator curves for each bus and time period.

<min> worksheet establishes the minimum value the source at each bus and time period can output. In a fixed operation case the minimum and maximum are equal.

<max> worksheet establishes the maximum value the source at each bus and time period can output.

DEMANDPREFERENCES.XLSX

The "DemadPreference.xlxs" spreadsheet has 9 worksheets within it of which 7 provide configuration information and <coef> and <work> worksheets provide support for demand preference polynomial and curve information.

<pref> worksheet establishes which bus will have an energy constraint and has information that must correspond for the number of buses and time periods.

<cost> worksheet establishes the polynomial for each bus and time period of the system

<fixed>worksheet is used to verify fixed demand values at each bus and time frame and corresponds to <min> and <max> worksheets. This spreadsheet was made obsolete and configuration can work without this for fixed values.

<energy> worksheet is used to configure the energy constraint for a bus which corresponds to the value of -100 in the cell in <pref> worksheet.

<min> worksheet establishes the minimum value the at each bus and time period can output. In a fixed demand operation case the minimum and maximum are equal.

<max> worksheet establishes the maximum value the source at each bus and time period can output.

<ancillary> worksheet is used to establish the maximum demand value at each bus and the step size for discretization in the algorithm.

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