# Optimization of combine processes using expert knowledge and methods of artificial intelligence

An der Fakultät Maschinenwesen
der
Technischen Universität Dresden

zur Erlangung des akademischen Grades
Doktoringenieur (Dr.-Ing.)

genehmigte Dissertation

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geb. am 10.07.1982 in Ravensburg

Tag der Einreichung: 09.03.2015
Tag der Verteidigung: 10.10.2017

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# Abstract

Combine harvesters are used to gather plants from the field and separate them into the components of value, the grain and the straw. The optimal utilization of existing combine potential is an inevitable task to maximize harvest efficiency and hence to maximize profit. The only way to optimize the threshing and separation processes during harvest is to adjust the combine settings to existing conditions. Operating permanently at optimal harvest efficiency can only be achieved by an automatic control system. However, for reasons of transparency and due to lack of sensors, the approach in this thesis is a combined development of an interactive and an automatic control system for combine process optimization.

The optimization of combine processes is a multi-dimensional and multi-objective optimization problem. The objectives of optimization are the harvest quality parameters. The decision variables, the parameters that can be modified, are the combine settings. Analytical optimization methods require the existence of a model that provides function values in dependence of defined input parameters. A comprehensive quantitative model for the input-output-behavior of the combine does not exist. Alternative optimization methods that handle multi-dimensional and multi-objective optimization problems can be found in the domain of Artificial Intelligence.

In this work, knowledge acquisition was performed in order to obtain expert knowledge on combine process optimization. The result is a knowledge base with six adjustment matrices for different crop and combine types. The adjustment matrices contain problem oriented setting adjustment recommendations in order to solve single issues with quality parameters. A control algorithm has been developed that is also capable of solving multiple issues at the same time, utilizing the acquired expert knowledge. The basic principle to solve the given multi-objective optimization problem is a transformation into one-dimensional single-objective optimization problems which are solved iteratively. Several methods have been developed that are applied sequentially.

In simulation, the average improvement from initial settings to optimized settings, achieved by the control algorithm, is between 34.5 % and 67.6 %. This demonstrates the good performance of the control algorithm.

# Contents

# Nomenclature

| | |
|---|---|
| $\alpha$ | concave clearance |
| $\dot{m}_{grain}$ | mass flow grain |
| $\dot{m}_{MOG}$ | mass flow MOG |
| $\dot{m}_{total}$ | total mass flow |
| $\rho_{straw}$ | density of straw on a walker |
| $c_1$ | constant representing straw type and condition |
| $c_2$ | constant representing initial aggregation of grain and MOG |
| $c_{mech}$ | constant for mechanical excitation of walker |
| $d_{grain}$ | diameter of grain |
| $d_{std}$ | diameter of standard threshing drum |
| $d_{td}$ | diameter of threshing drum |
| $E_n$ | energy needed per area of impact to detach a unit mass of grain |
| $F_{straw}$ | force expressing rigidity of straw |
| $l_{td}$ | length of concave |
| $l_{walker}$ | length of walker |
| $n_{td}$ | speed of threshing drum |
| $S_{acc}$ | accumulated separation |
| $v_x$ | transport velocity |
| $w_{td}$ | width of threshing drum |

| | |
|---|---|
| $w_{walker}$ | width of walker |
| $z$ | number of bars on the threshing drum |
| GPS | Global Positioning System |
| MOG | Material Other than Grain |
| QP | Quality Parameter |

# 1 Introduction and goals

## 1.1 Economic aspects of crop production

Production of agricultural goods is essential for the existence of mankind. Both the required amount of agricultural goods and their required quality are high. The main goal of a farmer is to achieve maximum profit. Figure 1.1 shows the main influencing factors on the total profit on the example crop production. The producer price and the production costs determine the profit per ton of sold crop. The multiplication of the profit per ton with the amount of harvested crop results in the total profit [1].


*Figure (1.1)* Factors that determine the total profit.

The producer price and the cultivated area are given factors. The producer price depends on the worldwide crop production and is therefore subject to variations that can not be controlled by a single farmer. The production costs, the yield and the harvest efficiency can be optimized by organizational and technical efforts. An increase in total profit can be achieved by a decrease of production costs, an increase in yield and an increase in harvest efficiency (figure 1.2). Here, harvest efficiency means the efficiency of the threshing and separation processes in the combine.

## 1.2 Reduce production costs

Increasing costs for raw materials and increasing labor costs have led to increasing production costs in recent years. Therefore the need for more efficient production pro-

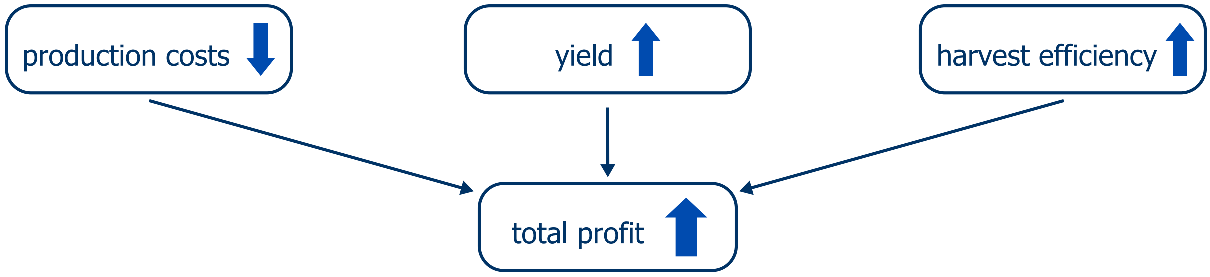



*Figure (1.2)* Possibilities to increase total profit.

cesses has emerged. Increasing costs for raw materials can be balanced with less consumption of raw materials. Increasing labor costs can be balanced by less employment of manpower. Both efforts require an organizational optimization of the cultivation and harvesting process and maximum availability of machines. This can be achieved by different actions (figure 1.3).

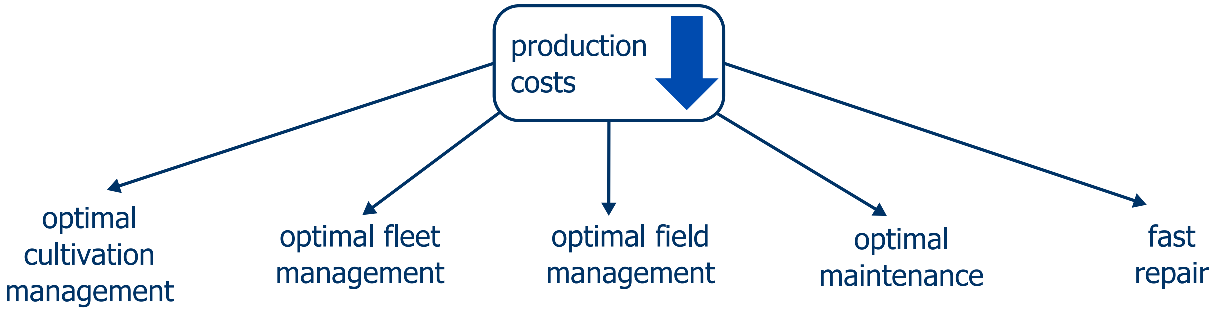



*Figure (1.3)* Possibilities to reduce production costs.

With cultivation management transport times can be minimized. Peaks during harvest can be avoided by a suitable selection of crop types and varieties [2]. Fleet management comprises the optimal coordination of all machines that are involved in the harvest, like combines and trailers[3]. Time is wasted if the combine has to wait for the trailer. The objective of field management is to minimize the distances traveled on one field. Maintenance is crucial for the full-time availability of machines. Careful inspections can avoid failures during harvest [4]. In case of a failure during harvest, immediate repair is necessary. Therefore, a functioning service network is essential. The diagnosis of the problem has to be performed quickly and spare parts have to be delivered fast.

## 1.3 Increase yield

The term yield describes the amount of crop per unit area that grows on the field. The yield which is collected by the combine harvester is referred to as harvested yield. The harvested yield depends on the yield on the field and the efficiency of the combine harvester.

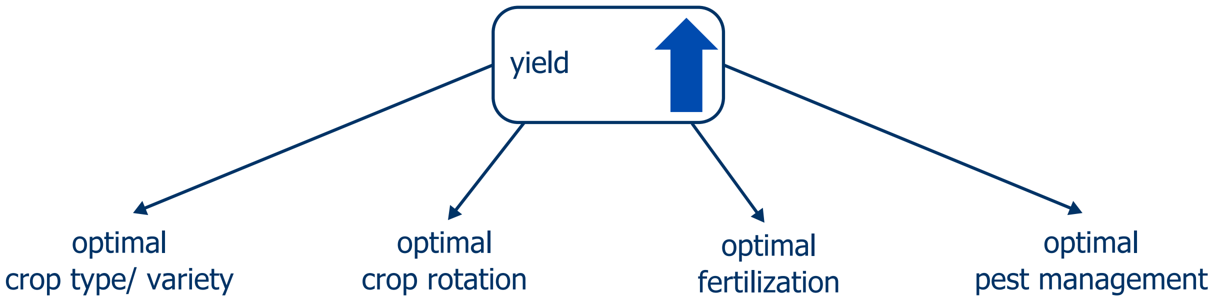



*Figure (1.4)* Possibilities to increase yield.

Four main factors determine the yield on a field (figure 1.4). Systematic breeding produces high-yield crop types and sorts. However, limitations are imposed by ethical concerns regarding genetic engineering. Additional demands on future crops are robustness against diseases, increased tolerance to drought and salinity and the reduction of agricultural inputs [5]. Crop rotation is a measure to preserve the soil's nutritive value and to keep it fertile. The use of fertilizer can increase yield by providing additional nutrition to the plants. Pesticides are utilized to fight against pests. However, excessive utilization of pesticides and fertilizer exploit the soil and hence have negative impacts on yield. In addition to that, there are legal restrictions that prevent excessive utilization of fertilizer and pesticides. Farmers that practice environmentally sustainable cultivation are disposed to even tighter restrictions. Precision farming supports the targeted utilization of fertilizers and pesticides [6]. Beside the increase in yield, precision farming also helps reducing production costs by minimizing the utilization of raw materials [7]. A further target of precision farming is a homogenous yield. On a homogenous field it is easier to exploit the combine's potential during harvest.

## 1.4 Increase harvest efficiency

Combine harvesters are subject to a variety of requirements, like high throughput, low grain loss, low damage of clean grain, high grain tank cleanliness, optimal straw quality and distribution. The minimization of grain loss and damaged kernels in the grain tank leads to a maximization of harvested yield. The cleanliness of the harvested grain influences the producer price. If additional cleaning in the mill is necessary, the achieved producer price is lowered. Additional cleaning of the harvested grain can be avoided by a higher cleanliness of the grain tank content. Throughput is a crucial factor for productivity. The higher the throughput of a combine, the less time is needed for harvest, and hence, the lower the labor costs are.

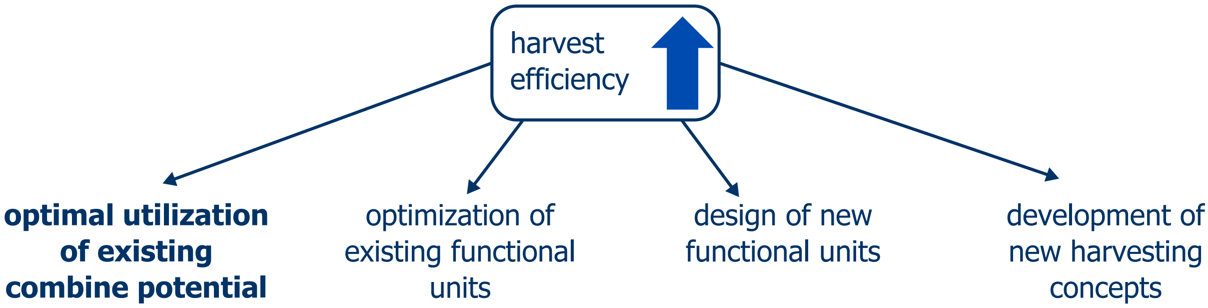



*Figure (1.5)* Possibilities to increase harvest efficiency.

Figure 1.5 shows the different ways to increase harvest efficiency. Mostly based on the analysis of crop flow in the combine harvester, existing functional units are optimized [8, 9, 10, 11]. Another approach to achieve higher harvest efficiency is the development of new functional units [12, 13]. The development of new harvesting concepts like a self-propelled header or a swarm of autonomous combines constitute revolutionary approaches to higher harvest efficiency. The new solutions are detached from the current solution of a man-driven self-propelled combine harvester that incorporates cutting, threshing, separation and residue management. Such new solutions do not only affect the harvesting process, they also affect the harvest logistics [14, 15, 16].

The increase of harvest efficiency is also possible based on existing technologies. The harvest efficiency - the efficiency of the threshing and separation processes - is influenced by the stage of maturity of the crop. An organizational activity to increase harvest efficiency is to choose the harvest time when the crop characteristics are optimal for harvest [2]. There are also machine based aspects that aim to increase harvest efficiency. Modern combine harvesters offer a diversity of settings. If these settings are not adjusted properly, the combine does not operate at maximum efficiency. The optimization of machine settings is absolutely necessary due to the huge number of influencing factors which the harvest process is exposed to, e.g. crop type, moisture and straw conditions. The complexity of the harvest process easily leads to maladjustment. Inexperienced operators hardly manage to find the settings that fully exploit the combine's capacity. Studies identified a loss of performance of 20-25% when comparing inexperienced operators to experienced operators [17, 18]. Even experienced operators happen to miss the goal of fully exploiting the combine's potential. As the machines become more and more complex, this will yet increase the divergence between available and actually utilized potential. The reasons which lead to unutilized machine capacity will be explained in detail in chapter 2.

## 1.5 Goals of this thesis

The combine's capacity is exploited fully only if the settings are adjusted optimally. The divergence of performance between experienced and inexperienced combine operators emphasizes the need for a *control system* that optimizes the harvest efficiency based on the existing combine technology. The optimized design of existing functional units, the design of new functional units or the development of new harvesting concepts do not treat the problem that the settings of the functional units have to be adjusted to existing conditions. Although a general goal of functional development is to reduce the number of settings, the actual trend shows an increase in the number of settings [19]. The *optimal utilization of existing combine potential* is an inevitable task to increase harvest efficiency and hence to increase profit.

The operator plays a key role during harvest. A control system that optimizes harvest efficiency must offer transparency. The actions taken by the control system must be traceable by the operator so that he is able to understand how the system is working [20]. An interactive assistance system that involves operator preferences and operator evaluations of harvest quality is the best way to gain the operator's confidence in the control system. The operator has to perform many tasks during harvest (see section 2.2.1). There are situations where he cannot focus on the optimization of the harvest efficiency. In this case an automatic control system is required.

The goal of this thesis is to develop *control algorithms that are suitable both for an interactive assistance system and an automatic control system*. As described above, there is the need for both kinds of control systems. In addition to that, the combined development of both control systems reduces development time and costs. For many crucial harvest quality parameters sensors are still being developed. The combined development of an interactive assistance system and an automatic control system provides the possibility to test the control algorithm without sensor information, using the interactive operating mode.

# 2 State of the art in combine process optimization

## 2.1 Functions and technologies of a combine harvester

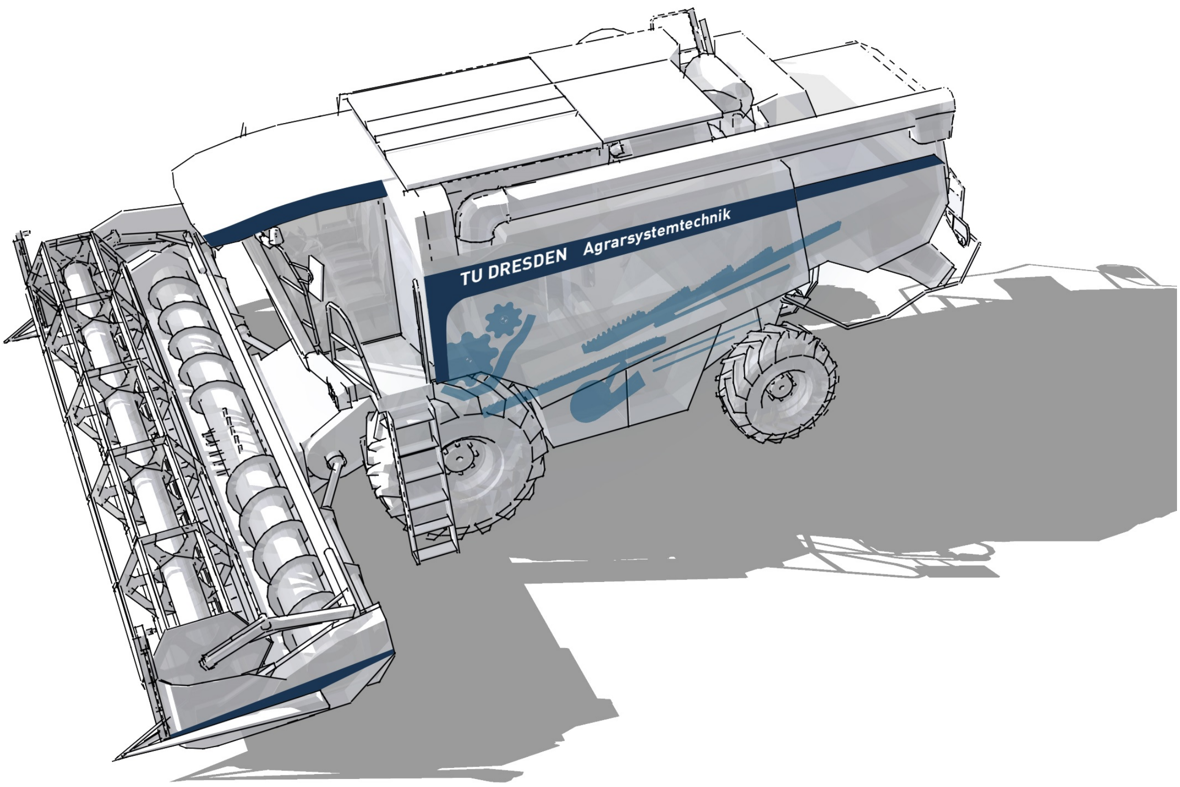



*Figure (2.1)* Combine harvester.

The overall purpose of a combine harvester (figure 2.1) is to gather the plants from the field and separate them into the components of value, the grain and the straw. This is achieved by performing the following main processing steps (or functions): cutting, threshing, separation, residue management and storing (2.2).

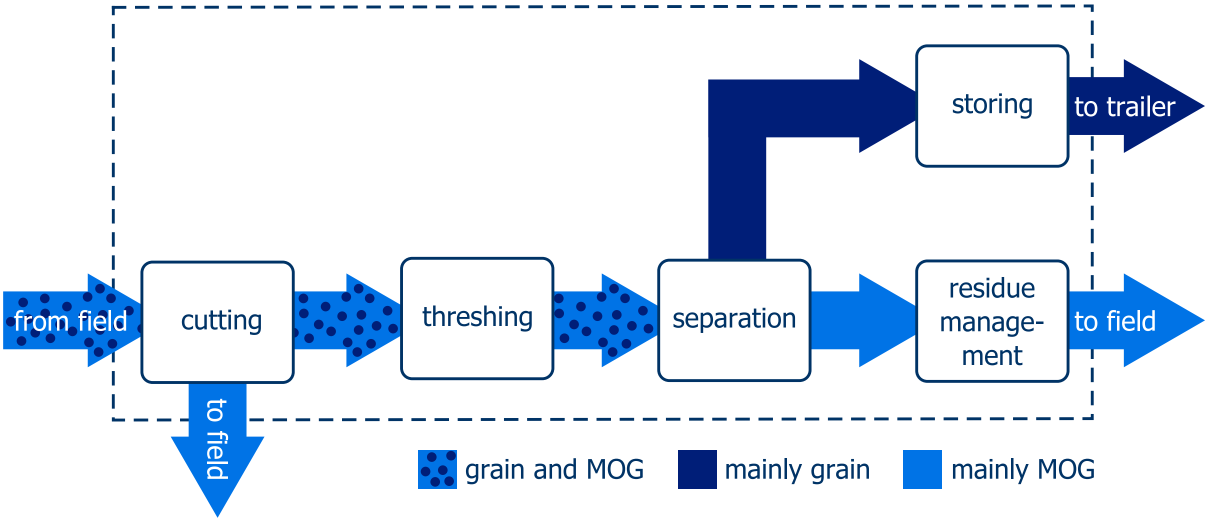



*Figure (2.2)* Main functions of a combine harvester.

Each function performs a special transformation of the mass flow. The mass flow components are listed in table 2.1. The components of value are undamaged free grain and straw, either chopped or as undamaged stems. However, it can not be avoided that each processing step (see figure 2.2) produces a certain amount of the unwanted components broken grain and lighter MOG particles. It is also not always possible to detach each grain from its ear. Hence, the mass flow that is distributed on the field as well as the mass flow that is transferred to the trailer contain all of the components listed in table 2.1.

*Table (2.1)* Components of the mass flow.

| component name | description |
|---|---|
| free grain | grain that is undamaged and detached from the plant |
| broken grain | damaged free grain |
| MOG | material other than grain (straw, stems, chaff, husks, weeds, ...) |
| unthreshed material | grain that is still attached to the ear |

For all of the functions different technologies are available. In addition to the main functional units of a combine harvester, there are elements for conveying the material. The main functions of a combine harvester, which are shown in figure 2.2, are described in more detail in the following subsections. Overviews of available technologies are the result of an internet study (year 2014) of the product ranges of the four market leaders in combine technology (Claas, John Deere, CNH, Agco).

### 2.1.1 Cutting

The first action in the functional chain of a combine harvester is cutting. A header cuts and gathers the plants from the field and forms them to a mass flow that enters the combine. Different types of headers can be attached to the combine (figure 2.3). Depending on the header type, either the complete plant or only parts of the plant enter the combine. In some applications the stems are left on the field, either as a whole or chopped. In this case the stems are a fertilizer for the soil. The combine is not charged with the stems which often constitute a significant mass portion of the plant. Thus, higher grain throughputs are possible. During cutting and conveying a certain amount of grain is already detached from the plants. In a standard grain header this is an undesired effect which can lead to unwanted shatter loss when free grain falls on the ground [21, 22, 23].

| process step / technology | cut | thresh | convey | chop |
|---|---|---|---|---|
| standard crop header | stem | no | whole plant | no |
| cornhead | stem | no | head | optional |
| sunflower header | stem | no | head | optional |
| stripper head | head | yes | head | no |
| pick-up head | - | no | whole plant | no |

*Figure (2.3)* Overview of process steps for different cutting technologies.

Figure 2.3 shows different cutting technologies. The standard crop header cuts the stems and conveys the complete plant into the combine. A cornhead cuts the stems and chops it to the ground. An alternative is to leave the stem as a whole on the field. The common feature is that only the cobs enter the combine. A sunflower header works similar to a cornhead. The stems are left on the field and only the heads enter the machine. With cornheads, sunflower headers and standard headers it is not intended to detach the grain from the head. Threshing is done in the threshing unit. In contrast, the purpose of a stripper head is to strip grain from the plants and leave the rest of the plant on the field. Most of the threshing is done in the header. The pick-up head is a special type which does not cut the plants but picks up a windrow and conveys it into the combine.

### 2.1.2 Threshing

The threshing process aims to detach the grain from the ear, capsule, husk, cob, ... of the plant. The incoming material is divided into the material components free grain, broken grain, unthreshed material and MOG. The material in the threshing unit is transported between a rotating element (threshing drum of axial rotor) and a concave. The compaction of the material and the relative velocities between rotating element and material flow, concave and material flow, and within the material flow itself produces a friction force that detaches the grain. Additional force is applied by the threshing elements of drum or rotor. The strikes of the threshing elements accelerate the grain which detaches from the plant and moves towards the concave. The threshing process is influenced by [8, 24, 25]:

- the direction and amount of force that is applied to the material,
- the velocity and the distribution of the material within the threshing unit,
- the design, number, dimensions and the position of the threshing elements,
- crop characteristics like crop type, crop moisture and the mass relation between grain and MOG,
- the settings of the threshing unit like the speed of the rotating element and the concave clearance.

The technologies for threshing are shown in figure 2.4. In state of the art combines the rotational speed of the threshing drum or rotor and the concave clearance (the distance between concave and rotor) can be adjusted from the combine cabin.

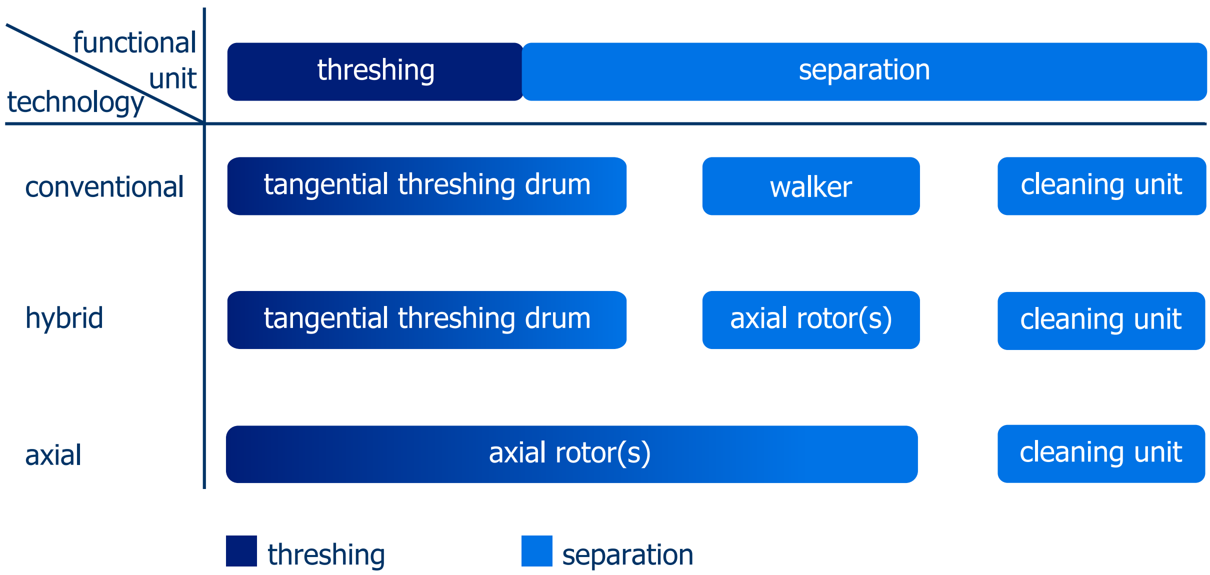



*Figure (2.4)* Technologies for the threshing and separation functions.

### 2.1.3 Separation

The goal of the separation process is to decompose the material flow into the components grain and material other than grain (MOG, e.g. straw, chaff, parts of the ears, weeds). This leads to a division of the material flow into several material flows. The separation process takes place in different phases, involving different functional units of the combine. In the first phase the material mat is loosened so that a relative movement between the components is possible. The components change their position due to different densities. The purpose is to locate the grain underneath the MOG particles. Depending on the utilized technology either gravity or centrifugal force is the main driver of the decomposition. A walker utilizes gravity, a rotational separator utilizes centrifugal force and the cleaning unit uses the combination between gravity and air flow. The separation of the components at a separation plane is the second step after the components have been decomposed. The geometric properties of the components in comparison to the properties of the sieve planes determine if the components fall through the plane. This is called sieving. The other physical principle to separate grain from MOG is wind separation. Lighter particles are blown out by the air flow through the sieves [12, 26, 27, 28].

The separation process depends on the characteristics of the material particles, like

- mass,
- moisture,
- aerodynamic properties (size, shape, density and orientation in the air flow),

the constructive properties of the involved functional units, like

- design of rotor/ threshing drum and concave,
- oscillation of walker and sieves,

and the settings of the functional units, like

- speed of rotor/ threshing drum,
- sieve openings.

The combination of these different properties determine for example

- the friction between particles,
- the intensity and direction of air flow

which are crucial factors for separation.

The threshing and separation process are closely connected to each other. In the tangential threshing drum both threshing and separation take place. Free grain that was detached by the threshing drum (=threshing) moves towards the concave and passes it (=separation). In a conventional combine, the proceeding separation steps are performed by the walker and the cleaning unit. In a hybrid combine, the walker is replaced by one or two axial separation rotors. In an axial combine the axial rotor performs threshing and the main part of separation. As in a conventional and a hybrid combine, the cleaning unit of the axial combine is responsible for final separation. The cleaning unit is mostly designed of two sieves that are placed above each other in combination with a fan to generate an air flow. The upper and the lower sieves are also called the chaffer and the sieve, respectively. Both chaffer and sieve opening, and the fan speed can be adjusted from the cabin. The mass flow portion that is separated at the lower sieve is conveyed into the grain tank. The portion that is not separated at the lower sieve is called the return flow (or tailings). The purpose of the return flow is to convey unthreshed material back to the threshing or separation section. The additional pass through the threshing and/ or separation section increases the probability that the unthreshed grain gets detached from the ears.

### 2.1.4 Storing

The material that is separated in the cleaning unit is transported into the grain tank for storage. The main part is free grain. Further components that reach the grain tank are broken grain, unthreshed material and MOG. Grain tanks up to 14,000 l are available on the market. An unloading auger conveys the grain tank content to a trailer.

### 2.1.5 Residue management

The material flow that does not reach the grain tank is transported out of the combine. This material consists mainly of straw, but also of free grain, broken grain unthreshed material and other MOG particles. One possibility of material handling is windrowing. The windrow is picked up in a separate operating step by e.g. a baler. The other possibility is to chop the straw and distribute it over the cutting width. For a good decomposition of the chopped straw on the ground, the chopped particles have to be short enough. Additionally, a high level of damage is important for an easy decomposition. The length and the level of damage of the chopped straw are influenced by [29]:

- straw moisture (the drier, the easier to chop),
- fertilization during growth,
- crop type.

For residue management a variety of configurations are available. One common configuration is a chopper in combination with discharge rotors. This configuration is used when large distribution widths are required. The speed of the rotors determine the distribution width. The offset between the rotor speeds determines the direction of the discharged material. The second common configuration is a chopper in combination with tailboard vanes and a separate chaff spreader. The chopped material is spread over the cutting width with the aid of the tailboard vanes. The vanes can be adjusted to adapt the distribution width to the cutting width. The angle of the vanes can be varied to change the direction of the discharged material. In this second configuration the chaff is discharged by a separate chaff spreader. The chopper consists of a shaft on which knifes are mounted. In modern combine harvesters the operator can switch between the two operating modes chopping and windrowing from the cabin.

## 2.2 Harvest process

The harvest process is the process of bringing the standing crop from the field. The combine separates the plants into the components that were described in the previous section. The efficiency of the above described combine functions determines harvest quality and harvest performance. The efficiency of the combine functions is influenced by the abilities of the combine operator, the available combine capacity, the combine settings and a variety of other influencing factors like crop and harvest conditions.

### 2.2.1 Tasks of the operator

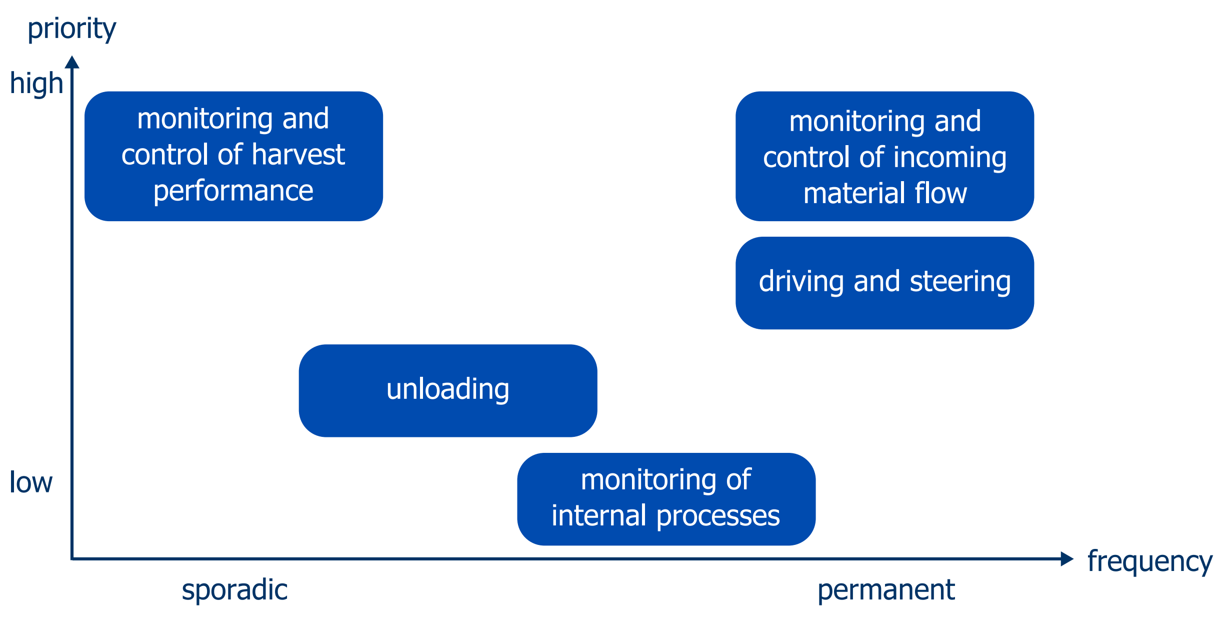



*Figure (2.5)* Frequencies and actual priorities of operator's tasks.

Figure 2.5 gives an overview about the tasks a combine operator has to perform. All of these tasks are required simultaneously which puts a high workload on the operator. A survey was carried out as a joint project by several chairs at TU Dresden in order to assess tasks and frequencies of operators. The survey included a video analysis over two complete harvest days. The results of the survey are in accordance with the author's own operator observations during several harvest seasons.

Monitoring and control of the incoming material flow is the task with the highest priority and highest frequency. The operator has to take care that enough but not too much material enters the combine. Header plugging and other issues concerning the header, like material that wraps around the auger or reel, have to be avoided. The operator can control the incoming material flow by adjusting forward speed and header settings. The higher the variations in yield, the more difficult it is to achieve a constant material flow. The threshing and separation units perform best when they operate at a constant mass flow. The more difficult the crop conditions are, the more difficult it is to get all the plants into the combine. Difficult conditions are for example lying plants. The higher the throughput, the more difficult it is to control the incoming material flow.

The task with the second priority is driving and steering. Provided that there are no issues with the incoming material flow, the operator tries to meet the edge of the standing crop with the edge of the header. The objective is to fully utilize the header width. The amount of required concentration depends on the forward speed of the combine and the header width. The higher the forward speed, the faster the operator has to react to disturbances. The larger the header, the more difficult it is to keep the edge of the header at the edge of the standing crop.

Unloading and monitoring of internal processes is the tasks with the lowest priority. The operator has to take care that all functional units work correctly. Issues can occur if combine settings are incorrect or elements, like transmission belts, are not operating correctly.

Monitoring and control of harvest performance has also highest priority although because this task is crucial for the overall profit. All of the functions described in the previous section, cutting, threshing, separation and residue management, have to be optimized. It is difficult to evaluate harvest quality because sensors that provide absolute values are not available. For some of the quality parameters there are no sensors at all. This means that the operator has to evaluate these parameters subjectively. The correlations between the influencing factors on the combine processes and the harvest quality are complex and partly unknown. Many of these influencing factors are exposed to continuous variation and are therefore hard to observe. Most of these influencing factors can not be measured, like grain to MOG ratio or threshing condition. A further difficulty is the large time delay between a change in input parameters and a change in the process output parameters. Hence, it is difficult to recognize the impact of an input change on the outputs. The response time of a change in yield to a change in grain throughput in the grain tank is about 20 seconds. It takes even longer until the operator is able to recognize the change in grain throughput. Monitoring and control of harvest performance is the most difficult task. This is the reason why it is performed with the lowest frequency, although it has highest priority beside monitoring and control of incoming material flow.

### 2.2.2 Harvest quality

The parameters that determine harvest quality are categorized into three major groups: grain losses, crop quality and residue quality (figure 2.6). Each group contains several parameters. The desired goal of the harvest process is to obtain low grain losses, high crop quality and high residue quality at the same time. However, the quality parameters are partly conflicting. Conflicts exist both between the categories and within one category. The improvement of one quality parameter can lead to the deterioration of other quality parameters.

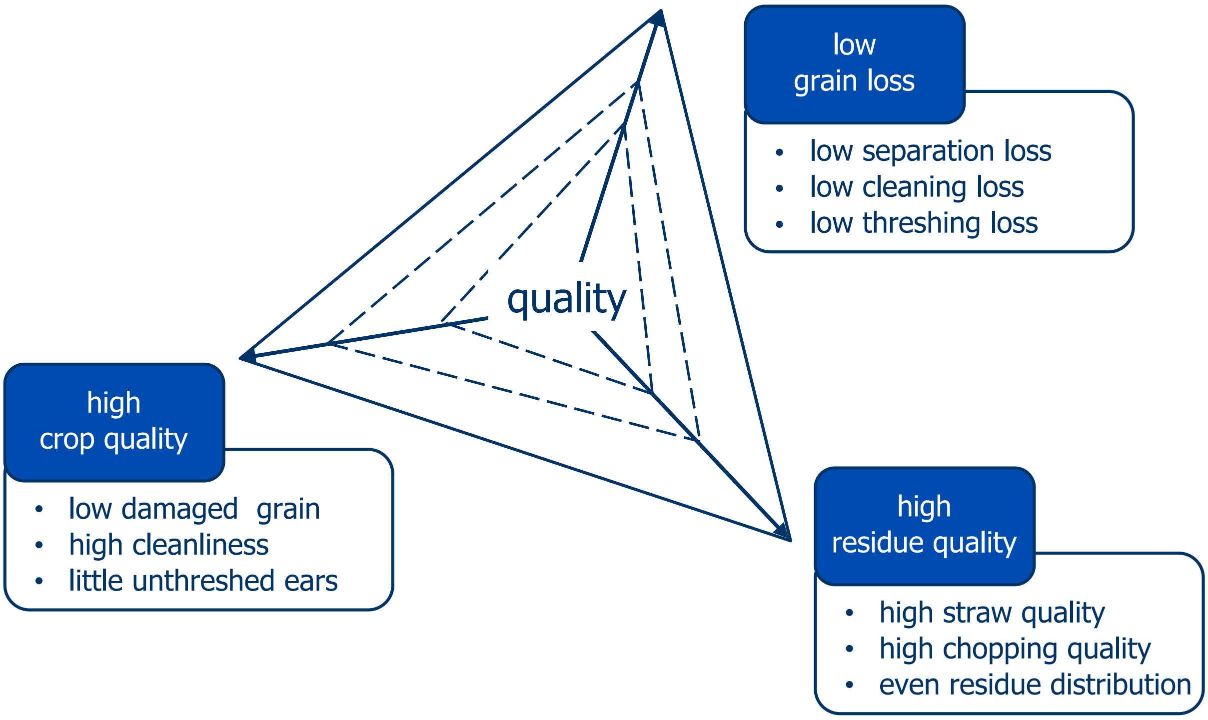



*Figure (2.6)* Parameters that determine harvest quality.

One important goal of the harvest process is to avoid grain losses. Grain losses can directly be transferred into a loss in profit. Each grain that does not reach the grain tank constitutes a financial loss. Grain losses can already occur at the header where the plants are cut and conveyed into the combine. Grain detaches itself from the ear and falls on the ground in front of the header. A more significant amount of losses emerges due to insufficient threshing and separation in the combine. Here, a distinction is made between separation loss, cleaning loss and threshing loss.

**Separation loss** is free grain that was detached from the ear in the threshing section but did not pass the straw mat in the separation section. Separation losses of a walker combine leave the machine via the walker. In an axial flow combine the amount of free grain that do not pass the grates of the separation section comprise the separation losses.

**Cleaning loss** is free grain that did not pass the upper sieve of the cleaning section.

**Threshing loss** is grain that was not detached from the ear. Threshing loss can either leave the combine via the separation section or the cleaning section.

The category crop quality describes the quality of the grain tank content. Crop quality comprises the parameters damaged grain, cleanliness (MOG) and unthreshed ears.

**Damaged grain** is subject to a reduced germination capacity and an increased sensitivity for diseases. The falling number, an index used to characterize the chemical properties, is also influenced by grain damage [30]. The crop producer receives a lower price if the degree of grain damage is above a defined threshold.

**Cleanliness** describes the relation between free grain in the grain tank and the amount of material other than grain (MOG). The term MOG summarizes all parts of the ear and the plant, like chaff, husks, cobs and stems, except the grain. The purchaser of the harvested grain cleans the grain from these impurities. If the amount of MOG is above the acceptable threshold, the crop producer is punished with a markdown.

**Unthreshed ears** are another kind of impurities in the grain tank. They are considered separately as they both consist of grain and MOG. Unthreshed ears are ears or parts of an ear that still contain grain.

The third category of quality parameters is the residue quality. This category mostly has the lowest priority as its impact on the revenue is low. The residue quality is determined either by the straw quality or by the chopping quality and distribution.

**Straw quality** is determined by the degree of damage of the straw.

**Chopping quality** comprises the length of the chopped straw and the degree of fanning out. The requirements on the chopping length and the fanning out are determined by the kind of soil cultivation the farmer applies. A better fanning out supports the rotting of the chopped straw. Shorter straw parts are easier to mix under the soil.

**Residue distribution** is the distribution of the chopped material behind the combine.

An even distribution over the complete cutting width is desired to provide an even fertilization of the soil. In addition to that, the chopped material should not be blown into the standing crop.

### 2.2.3 Harvest performance

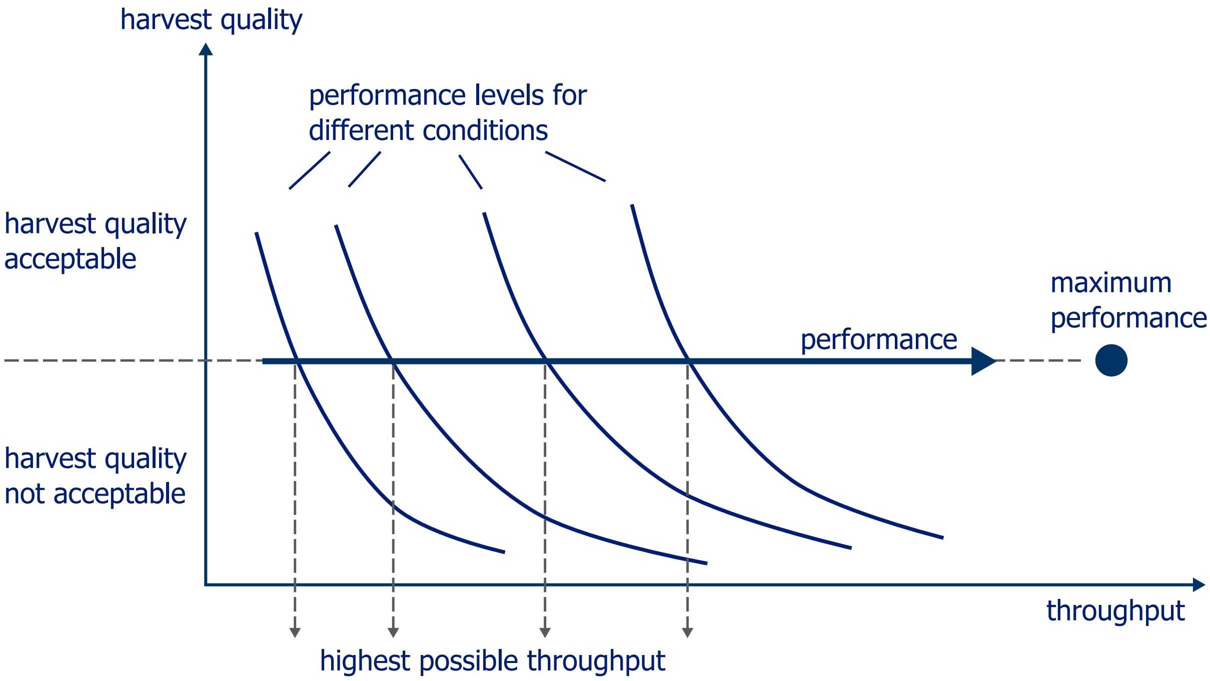



*Figure (2.7)* Harvest quality as a function of throughput. The current performance level determines the highest possible throughput.

Harvest quality in relation to the time needed for harvest determines the harvest performance. Throughput is used as a measure of the time that is needed for harvest. The higher the throughput, the higher the productivity, the lower the time needed for harvest. This implies that the higher the throughput the higher the harvest performance. However, there exists a negative correlation between harvest quality and throughput as shown in figure 2.7 [31, 32]. When operating on the same performance level, the highest possible throughput is determined by the lowest acceptable harvest quality.

An overview of influencing factors on the performance level is shown in figure 2.8. The crop characteristics and the harvest conditions can not be influenced by the combine operator during harvest. Crop characteristics comprise parameters like moisture, thousand kernel mass, crop to MOG ratio, threshability, straw condition and yield. Harvest conditions are e.g. weather, ground and field conditions. The combine and header type can not be modified during harvest. However, the combine or header type can be selected to meet the regional conditions and the farmer's preferences for quality

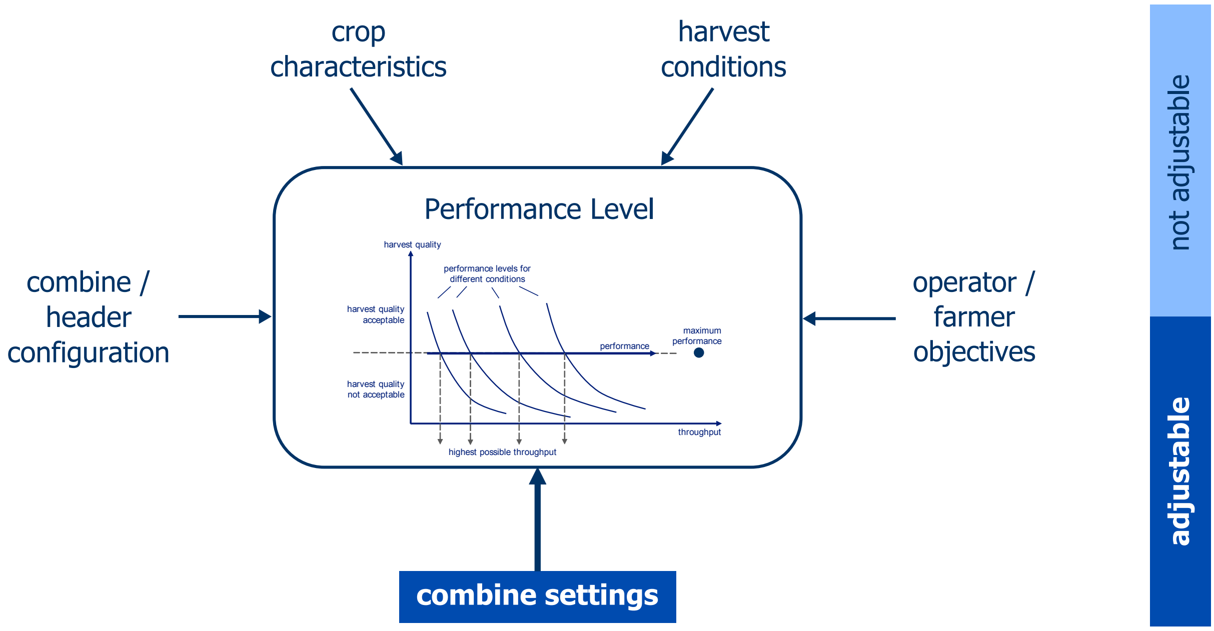



*Figure (2.8)* Influencing factors that determine the performance level [2, 17].

parameters before harvest. To a certain degree, harvest conditions can be influenced indirectly by the choice of the harvest time. Over daytime harvest conditions and crop characteristics vary in a certain range. In the evening hours when moisture increases, performance is shifted to a lower level.

Combine settings have a direct impact on the performance level. Combine settings are divided into two main categories: in-cab settings and out-of-cab settings. The operator can adjust the in-cab settings on a control panel in the cabin. A higher effort is needed to change out-of-cab settings. The operator has to leave the cabin to perform a mechanical adjustment. Tools and/ or additional parts may be required.

> Increasing the performance level is equivalent to an increase in harvest efficiency. For an increase in performance it is necessary to optimize the threshing and separation processes inside the combine. The only way to optimize these processes during harvest (and based on the existing technology) is to adjust the combine settings to existing conditions. However, finding the optimal settings is a challenging task.

### 2.2.4 Challenges of process optimization

The influencing factors from figure 2.8 not only affect the harvest performance level, they also determine the optimal combine settings. The influencing factors are partly unknown (figure 2.9).

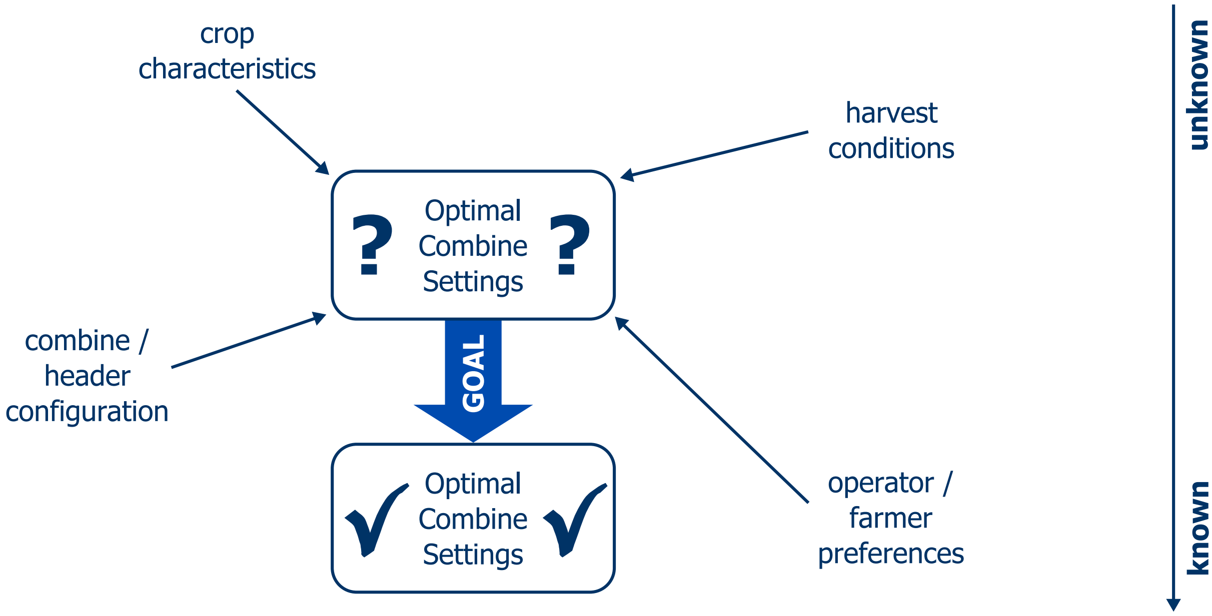


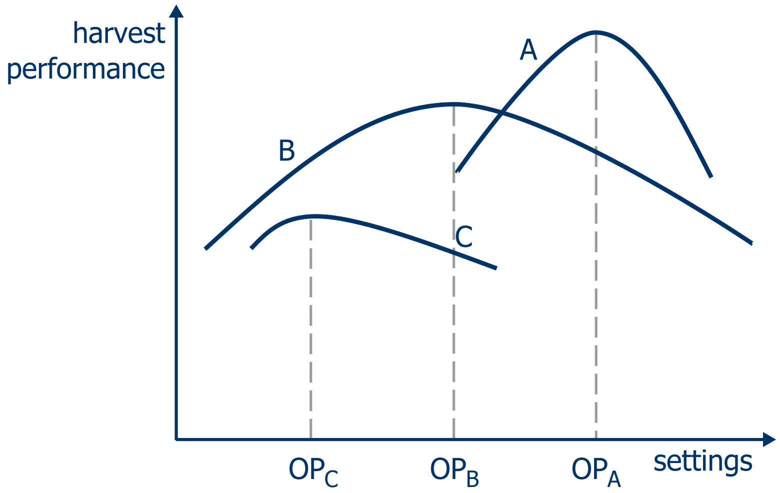

*Figure (2.9)* Optimal combine settings are a function of known and unknown factors.

For most of the parameters, both the parameter values and the impact on the threshing and separation processes is unknown. Correlations between crop characteristics and harvest performance are complex. Direct correlations could be detected most clearly for moisture and grain to MOG ratio [33]. The harvest conditions can be evaluated by the operator. He can e.g. see if the crop is standing or lying on the ground. He can also measure the air humidity which influences the crop and straw moisture. The impact of harvest conditions on harvest performance is determined by complex unknown correlations. The operator knows his combine and header configuration. He does not know which impact e.g. the dimensions of threshing drum or sieve have on harvest performance. However, an experienced operator develops a feeling for his combine and intuitively assesses the characteristics of the threshing and separation elements. Operator and farmer preferences are known. They determine the harvest goals which in turn are a crucial factor for the optimal combine settings.

As a consequence of the variety of influencing factors

- the range of relevant settings,
- the location of the optimal operating point (optimal settings),
- the peakedness of the performance maximum and
- the achievable performance level

are different depending on the conditions. Curve A in figure 2.10 shows a very clear peak. A deviation from the optimal operating point results in a strong deterioration of performance. Curve B is smoother and has a larger range. Due to the larger range the




| | peak | range |
|---|---|---|
| A | strong | small |
| B | weak | large |
| C | very weak | small |

*Figure (2.10)* Harvest performance as a function of settings for different influencing factors (curves A, B and C).

optimal operating point is harder to find. The deterioration of performance when deviating from the optimal settings is weaker as for curve A. Curve C shows the smoothest characteristic. The deviation from the optimal operating point results in an insignificant deterioration of performance. However, there is hardly any potential to improve performance by optimizing the combine settings, due to the smooth characteristic.

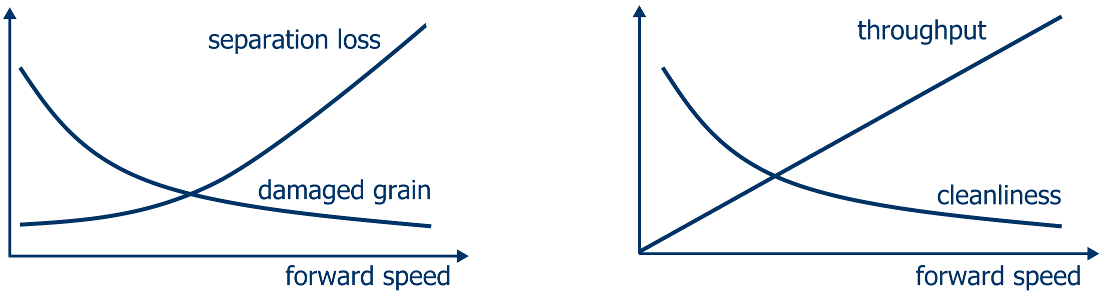



*Figure (2.11)* Two examples of conflicting quality parameters.

The conflicting quality parameters were already introduced in section 2.2.2. The change of a setting can result in an improvement of one quality parameter while another one is deteriorated (figure 2.11). When forward speed is increased the amount of damaged grain in the grain tank is reduced while separation losses normally rise up. A high forward speed leads to a high throughput which is essential for a high performance. However, high throughput is accompanied by a low cleanliness.

> Determining the optimal settings to achieve highest possible performance is a challenge because:
>
> - there is a huge number of influencing factors,
> - the impact of the influencing factors is often unknown,

- influencing factors underlie permanent variations,
- the value of the influencing factors is mostly unknown, and
- quality parameters are conflicting.

## 2.3 Support for the operator to reduce the workload

Automatic control systems are available for automatic steering, throughput and loss control and inclination compensation. Automatic steering is supposed to provide a uniform material flow due to a constant cutting width. Less overlapping of the lanes saves time and fuel. Automatic steering also avoids that stripes with crop remain on the field. The control signal can either be optical, mechanical [34], or GPS based [35]. A constant material flow produces a uniform utilization of the combine's functional units. Forward speed is adjusted to keep throughput constant [36]. Some manufacturers offer the option to adjust throughput with respect to losses [37]. The automatic compensation of the ground inclination has the intent to distribute material uniformly on the width of a functional unit for better utilization of the unit's capacity.

## 2.4 Support for the operator in performance optimization

Training is the basic method to prepare the operator for monitoring and control of the harvest performance. Basic knowledge on combine functionality and adjustment of settings is delivered either by manufacturers or independent consultants [30]. However, a basic training can not prepare the operator in a way that the appropriate knowledge is available immediately when it is needed during harvest. Several years of experience are necessary until supervising and control of all combine processes is intuitive. As harvest is a seasonal activity, it takes time for the operators to familiarize with the machine each new season.

Basic settings or setting ranges for different machine types, crop types and conditions are provided by the manufacturers. They are either available in the combine's information system or in the manual. These settings constitute average values that provide acceptable results in a wide range of harvesting conditions. Thus, they only provide optimal solutions for a few conditions [38].

Combine harvesters are equipped with loss and return flow sensors, providing relative information on the loss level and the return flow. Their main benefit is to display a relative change in loss or return flow level. For calibration a reliable reference, a measurement of losses (e.g. with loss pans), is necessary. The displayed loss sensor values then represent absolute loss. There is the risk that the importance of calibration is ignored and the displayed values are taken too seriously. In 2013 a camera was introduced which takes pictures of the grain tank content [34, 39]. The different components like damaged grain and MOG are marked with different color. A relative display value is also provided, similar to the relative loss display. An absolute value of the mass percentage of damaged grain, MOG and unthreshed material in the grain tank is not provided. Research is done on sensing the straw quality in the windrow [40]. On the market, a sensor for straw quality is not yet available.

Independent consultants offer their know-how on combine optimization. They can be hired to assist the operator while harvesting. However, it is unlikely that a single expert is familiar with all existing machine types, crop types and conditions. Alternatively, remote assistance can be requested. For this purpose CAN bus data is sent from the combine to a server. A supervisor analyzes the combine performance and gives feedback on necessary adjustments [41]. However, the evaluation of performance is limited as important data on harvest quality is missing. Evaluation is done based on forward speed, grain yield and fuel consumption. Information on absolute loss and grain tank quality is not available. In addition to that, an expert on the field takes into account threshing condition, straw condition and other information that can not be measured. These data are important for decision making. Telematics services provide a network in which operators can compare their settings and performances with other operators [34]. Comparing performance only makes sense if combine types, yield and conditions are similar. A great benefit can only be achieved if a combine with significantly higher performance exists as reference.

Various patents have been published that describe approaches for process optimization. There are basically two different approaches. The patents [42, 43, 44, 45] describe interactive control algorithms which use operator evaluation and operator satisfaction for the relevant quality parameters (losses, grain quality and straw quality). In [45] the operator has to rank the quality parameters. In [42, 43, 44] the operator has to decide on the major strategy of the control, like high throughput or high grain quality. The control system is started as soon as the operator states that he is not satisfied with a quality parameter. Only one quality parameter can be selected. The system determines settings adjustments based on expert knowledge. Another approach uses sensor information to evaluate quality and process parameters. These automatic control systems are described in patents [46, 47, 48, 49, 50, 51, 52, 53] and in the articles [54, 55, 56]. The approach described in [52, 53] utilizes expert knowledge. In [46, 47, 48, 49] characteristics between combine settings and some of the relevant quality parameters are generated. The measured characteristics for separator loss, cleaning loss, return flow volume and free grain in the return flow are utilized to determine the optimal settings for the separator and the cleaning unit. Grain quality is not considered. Separator and cleaning unit are considered as detached units.

## 2.5 Conclusions

For an increase in performance it is necessary to optimize the threshing and separation processes inside the combine. The only way to optimize these processes during harvest is to adjust the combine settings to existing conditions. However, finding the optimal settings is a challenging task. Of all the tasks the operator has to perform (figure 2.5), the monitoring and control of the harvest performance is the most complex task. It is the task with highest priority but which is carried out with the lowest frequency. This means that the operator will first focus on monitoring and control of the incoming material flow, on driving and steering, on the monitoring of internal processes and on unloading. When there is time left, the operator will take care of the monitoring and control of harvest performance. The amount of concentration the operator can spend on this task is very limited and actions can only be taken randomly.

There are solutions that aim to reduce the workload on the operator. By using automatic steering or throughput control the available time for monitoring and control of the harvest performance is increased. Harvest performance can be checked more frequently and therefore adjustments of the combine settings will be done more often. However, permanent monitoring and control of harvest performance by the operator can not be reached. Furthermore, monitoring and control of harvest performance has still least priority.

Permanent monitoring and control of harvest performance can only be reached by an automatic control system. The adjustment of combine settings has to be done in the background, keeping operator interactions at a minimum. However, for the reasons described in section 1.5 (traceability, gain operator's confidence, lack of sensor information) the approach of this thesis is a combined development of an interactive and an automatic control system. There is no solution on the market that optimizes the entire threshing and separation process in a comprehensive manner. The existing automatic control system described in patents [46, 47, 48, 49] is built of different control agents for the separation process in the axial separator and the cleaning unit. The control algorithm uses a model-based control strategy which is difficult to trace by the operator. The corresponding interactive solution described in patents [42, 43, 44] uses a completely different control strategy based on expert knowledge. The operator can only focus on the improvement of single quality parameters. The goal is not the optimization of the overall combine quality.

In the next chapter an overview of existing models of the threshing and separation processes is given. The existing models are evaluated with respect to their applicability in a control system for process optimization.

# 3 Approaches for describing combine processes

A variety of models that represent the internal combine processes have been developed. The purpose of the current chapter is to give an overview and to evaluate the models with respect to their applicability in a control system for process optimization.

In this work they have been categorized into partial mathematical models, comprehensive mathematical models and comprehensive qualitative models. A model that can serve as a basis for a control system for process optimization has the following requirements:

1. All parameters that determine the harvest quality and the combine's performance (e.g. clean grain mass flow, losses, damaged grain, unthreshed material in grain tank) have to be represented as model outputs.
2. All relevant combine settings have to be represented explicitly.
3. All model parameters have to be known.

The following sections comprise a baseline study on relevant existing models that can be used for the control system which shall be developed. Based on the existing models, consequences for relevant optimization methods are drawn at the end of this chapter.

## 3.1 Partial mathematical models

Partial mathematical models concentrate on an isolated part of the internal combine process. The main goal is to characterize the separation function of efficiency at a certain location, and partly to derive relationships for first order quality parameters.

TROLLOPE [57] models the threshing process in a tangential threshing drum. The physical equations that are the fundamental of his model are:

- the equation of continuity,
- Newton's second law (impulse),

◦ Hooke's law (deformation under pressure).

The result is a set of six equations which contain seven unknown process parameters and several unknown constants. The unknown process parameters are the pressure on the material depending on the angle within the threshing drum, the distance between the concave and the threshing drum, the velocity of the material at a certain angle and four geometrical parameters. The constants in the model depend mainly on throughput and friction within the threshing drum. The values are derived by regression on experimental data. Explicit relationships between the constants and their influencing factors like throughput are not derived.

GREGORY's approach [58] to model the accumulated separation $S_{acc-td}$ in a tangential threshing drum is a combination of a probabilistic and a physical approach. GREGORY states that the rate of threshing decreases as the probability of hitting unthreshed grain decreases. Thus, the cylinder speed $n_{td}$, the number of bars on the cylinder $z$ and the length of the concave $l_{dt}$ play an important role in his model:

$$S_{acc-td} = e^{f1}, \tag{3.1}$$

$$p1 = \frac{l_{td} d_{std}}{\alpha d_{td}}, \tag{3.2}$$

$$f1 = -\frac{\dot{m}_{grain}}{\dot{m}_{MOG}} \cdot \frac{F}{E_n} \cdot \frac{w_{td} n_{dt} z}{\dot{m}_{total}} \cdot (0.146 + 0.00139 \cdot p1) \cdot \left(1 - e^{-0.176 \cdot p1}\right). \tag{3.3}$$

GREGORY [59] also modeled the accumulated separation of a walker. Similar to equation 3.4 the model for separation in the walker explicitly contains design and crop characteristics, and operating parameters of the walker:

$$S_{acc-walker} = 1 - e^{f2}, \tag{3.4}$$

$$f2 = -l_{walker} \cdot \frac{c_{mech} w_{walker} v_x \rho_{MOG}}{d_{grain}^2 \dot{m}_{MOG}} \cdot e^{-c_1 c_2 \frac{\dot{m}_{MOG}}{w_{walker} v_x}}. \tag{3.5}$$

MIU et. al [60, 61] selected a probabilistic approach for their model of grain threshing and separation in tangential and axial threshing units. The model describes the fraction of free grain, separated grain and unthreshed grain over the length of the concave (tangential threshing drum) or the rotor (axial threshing unit). Hence, the threshing and separation losses in the threshing unit can be quantified. As an example, the threshing loss is described as

$$V_S = \frac{\lambda}{\lambda - \beta}(e^{-\beta L} - e^{-\lambda L}). \tag{3.6}$$

The variable $L$ is the length of the concave or the rotor. The variables $\lambda$ and $\beta$ are determined by regression on experimental analysis. $\lambda$ and $\beta$ depend on parameters such as crop type, grain to MOG ratio, material velocities and throughput, design parameters and settings of the threshing unit (concave clearance, cylinder/ rotor speed). Explicit relationships between these real process parameters and the model parameters $\lambda$ and $\beta$ are not derived.

BÖTTINGER [27] derived the separation function $Z$ of walker and sieve over the length of the element:

$$Z(l) = \frac{A \cdot B}{B - A} \cdot l^D \cdot (e^{-\frac{B}{D+1} \cdot l^{D+1}} - e^{-\frac{A}{D+1} \cdot l^{D+1}}). \tag{3.7}$$

The basis of his derivation is a physical model which represents the decomposition of the material flow and the separation. With his model, BÖTTINGER is able to determine walker and cleaning loss. The parameters $A$, $B$ and $D$ of the derived separation function are determined by regression. Direct influencing factors on the separation process, such as sieve opening and crop characteristics, are incorporated implicitly in these parameters.

FREYE [26] developed the equation of motion for a material mat on a sieve plane which is inclined in longitudinal direction and which is excited with a sine oscillation. The forces on the particles in the material mat strongly depend on the mechanical, geometric and aerodynamic crop properties of the single material components. Before FREYE's equations can be used, these physical crop properties have to be determined. Due to the inhomogeneous composition of the material mat, the mechanical, geometric and aerodynamic crop properties vary in a wide range. FREYE's model makes it possible to determine:

- the transport velocity,
- the ratio of decomposition,
- the relative distance between the material mat and the sieve and
- the velocity with which the material mat falls on the sieve.

Experimental investigations showed that the derived model delivers accurate results, provided that the physical crop properties were determined appropriately. However, the model in only valid for the fluidized state, and not for the overblow phase or the compaction phase.

HÜBNER [12] optimized FREYE's equations of motion by integrating the characteristics of the air flow. He integrated the flow resistance of the sieve and the material on it, and hence, the deflection and the air distribution. With this model, both qualitative and quantitative changes of the transport velocity, the ratio of decomposition, and the other parameters of the above listing can be be determined when design and operating parameters are varied. HÜBNER also developed a three dimensional motion model for a rotating cleaning unit. The model takes into account the slip between the cleaning rotor and the material mat and the aerodynamic force onto the material mat. Mechanical, pneumatic and design parameters of the rotating cleaning unit can be varied. Experimental investigations showed high accordance between measured data and model data.

CRAESSAERTS et al. [62, 63, 64, 65] developed a method to estimate the impact which different parameters have on the harvest quality. They applied this method to predict the percentage of MOG in the grain tank and the sieve losses in the cleaning section. The result is a linear equation with two or three abstract parameters, which have to be determined by regression:

$$MOG = (a_M \cdot FanSpeed) + (b_M \cdot PressureSieveFrontLeft) + c_M \quad (3.8)$$

$$Sieve\ Loss = (a_S \cdot PressureSieveRearLeft) + b_S \quad (3.9)$$

The pressure under the upper sieve represents the load in the cleaning section.

> The partical mathematical models concentrate on an isolated part of the threshing and separation process. All of the described models are steady state models that do not represent the dynamic behavior. A combination of these partial models will not deliver a comprehensive model that contains all crucial quality parameters. For example, there is no model that describes the amount of unthreshed material in the grain tank. In addition to that, the models use different numbers and kinds of parameters which would make it difficult to combine the partial models. The partial models have in common that they require a calibration of model parameters. Thus, the models cannot be used directly for process optimization.

## 3.2 Comprehensive mathematical models

In contrast to partial models, comprehensive mathematical models comprise the entire combine process from the incoming mass flow to the output mass flow. Analytical equations or transfer functions are used to describe the handling of the material flow.

BECK [66] set the focus on stationary state behavior of the material flow. His work is a combination of a physical, empirical and probabilistic approach. He divided the threshing and separation process in the combine into several partial processes. For each partial process he determined the accumulated separation , taking into account the degree of decomposition of grain and MOG at the beginning of the corresponding partial process. The model contains the mass flow components grain and MOG. Broken grain and unthreshed material are not considered. BECK conducted laboratory experiments to verify his model. The model parameters are determined by adapting the model equations to measured accumulated separation. The model parameters implicitly contain crop characteristics, design properties and machine settings. Thus, the model is valid for a single operating point. The calibration of the model to a given operating point requires great effort.

BERNHARDT [21] analyzed the time domain behavior of the combine process. The considered mass flow components are grain and MOG. The transfer functions for the grain mass flow in the partial processes are modeled as a combination of a first order time delay and a transport delay. The parameters of the first order time delay elements incorporate crop characteristics, combine settings and other influencing factors. An experimental analysis was conducted to determine the model parameters.

HERLITZIUS [67] modified BERNHARDT's model. The parameters of the transfer functions are characterized in more detail by theoretical and experimental analysis. Additionally, the valid ranges of the parameters, the parameter variances with respect to time and the influencing factors that lead to these variances were determined. Due to the various variances, the model has to be adapted to existing conditions and machine settings.

MAERTENS et al. [68, 69] developed an analytical grain flow model with the purpose to use the model for evaluation of yield mapping systems. The model comprises the material flow from the header up to the grain tank. Grain separation efficiencies and distributions are represented by means of probability density functions. Design parameters and velocities of rotational and conveying elements have been considered. Combine settings have not been considered. The final analytical equations for the model functions have not published.

CAMPBELL [70] mounted a number of sensors on a conventional combine harvester to measure ground speed, table auger torque, cylinder torque, walker grain loss, sieve grain loss and the return grain flow. The measured data was used to calibrate his combine model which was written in Fortran. The model represents the dynamic behavior of the three mass flows straw, chaff and grain. The dynamic characteristics are implemented by first order time delays and transport delays. CAMPBELL also derived analytical equations for separation. He considered design parameters and physical parameters like the wind velocities under the sieves. However, the basic combine settings are not explicitly incorporated. A deficiency of the model is the necessity of a reference measurement in normal crop conditions to perform a first calibration of the model. A further weakness is that for a number of model parameters measured values are not available. Thus, assumptions have to be made.

> The comprehensive mathematical models comprise the entire combine process from the incoming mass flow to the output mass flow. Some of the models contain the dynamic behavior of the material flow(s). Analytical equations or transfer functions are used to describe the handling of the material flow. The models concentrate on the grain separation at the various functional units. MOG separation, broken grain and unthreshed material are mostly neglected. None of the described comprehensive mathematical models fulfills all requirements stated in the introduction.

## 3.3 Comprehensive qualitative models

There exists no model that fulfills all three requirements that have been listed in the introduction of this section. However, there exists a comprehensive qualitative model that describes the main quality parameters (separator loss, cleaning loss, ...) as a function of the most important influencing factors, which are crop characteristics and combine settings. The correlations between combine settings of a walker combine, several crop characteristics and process parameters can be found in [71, 72]. The model consists of two-dimensional (single input - single output) characteristics. An example of such a two-dimensional characteristic is given in figure 3.1.

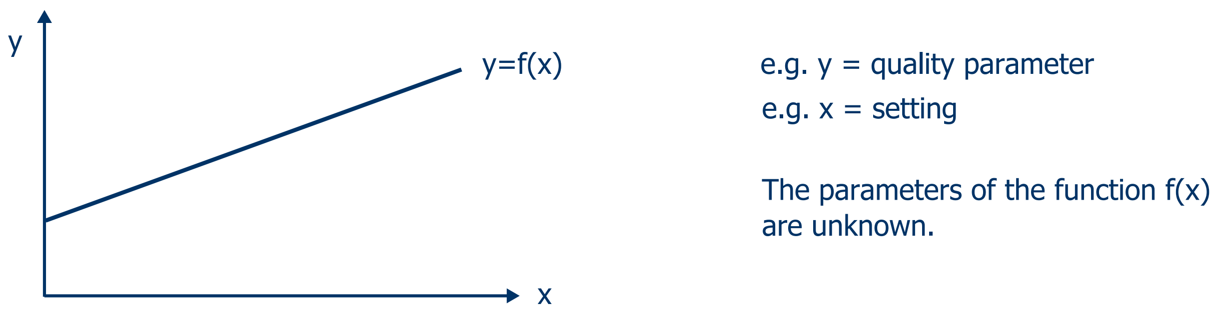



*Figure (3.1)* Example characteristic between an influencing factor (e.g. a setting) and a process parameter (e.g. a quality parameter).

The characteristics between the combine settings, crop characteristics and process parameters can be of different form. The common analytical equations that are used are shown in figure 3.2. The slope of the characteristics (b), (c), (d), (e) and (g), which do not have an optimum, can also be negative. The absolute values of the parameters $a$, $b$ and $c$ of the equations depend on the various influencing factors that have been described in the previous chapter, such as crop moisture and threshing condition. The location of the optimum of characteristics (f) and (h) also depends on these influencing factors. A qualitative model comprises the general shape of the two-dimensional relationships. The parameters $a$, $b$, $c$ of the function are unknown.

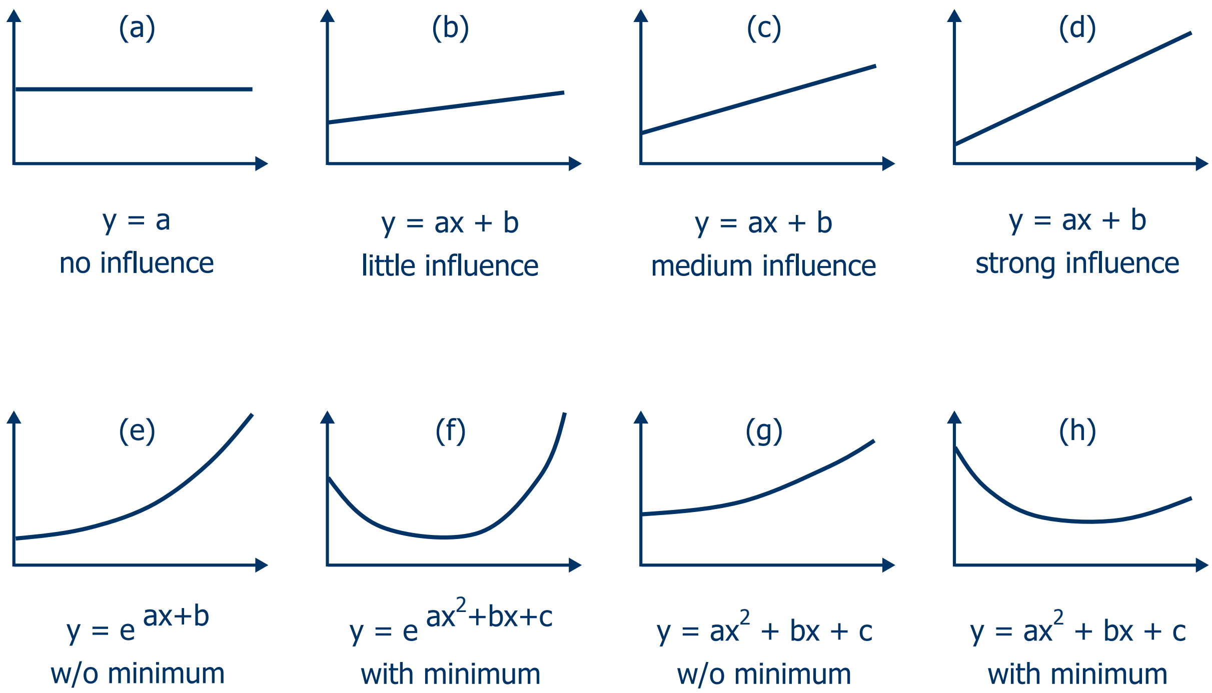



*Figure (3.2)* Overview of different types of characteristics between influencing factors and process parameters.

A comprehensive overview of the correlations between combine settings and the most important process parameters is given in figure 3.3. Most of the process parameters are influenced by all of the combine settings. Straw damage is the process parameter with the lowest number of influencing settings. Figure 3.3 also shows that forward speed, thresher speed and concave clearance have impact on all of the listed process parameters. The sieve opening is the setting with the lowest number of influenced process parameters. Only five of the nine listed process parameters are influenced by the sieve opening. The goal of combine process optimization is to find the minimum of all of the process parameters. The different signs of the slopes of the characteristics demonstrate the conflict between the process parameters. There is no setting in figure 3.3 whose characteristic has the same sign for all of the process parameters.

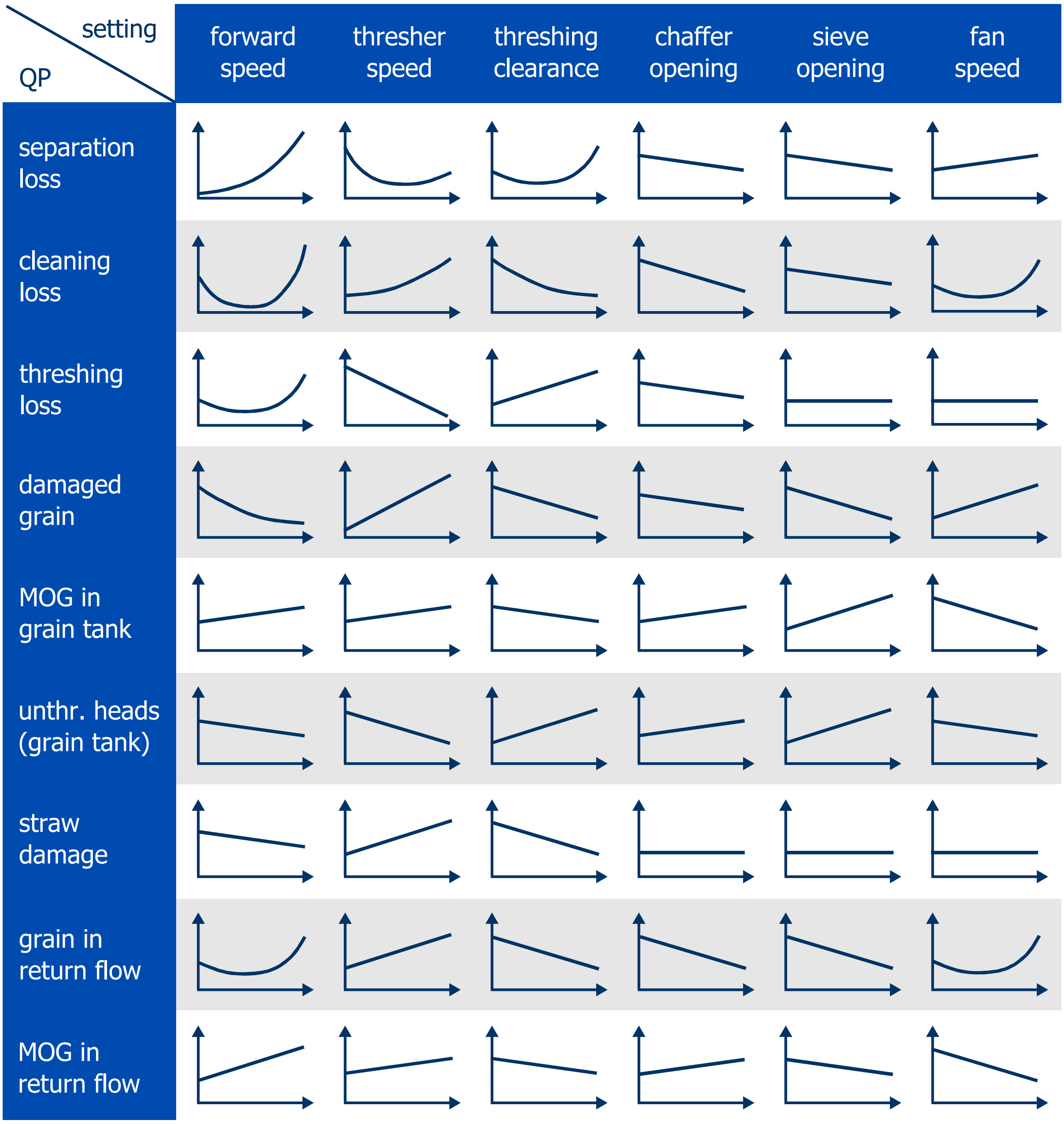



*Figure (3.3)* Correlations between combine settings and process parameters.

As an example, at higher thresher speeds, more grain is detached from the heads as there are more impacts on the grain and higher forces. Thus, threshing losses and the amount of unthreshed heads in the grain tank decrease while grain damage increases. Higher thresher speeds cause a higher separation of MOG particles. This means more straw damage, more MOG in return flow and more MOG in the grain tank. As the overall amount of MOG particles in the combine increases, the load on the cleaning unit increases, and as a consequence cleaning losses increase. For very high thresher speeds the separator is overloaded by MOG particles which leads to reduced separation and therefore more separation losses. Otherwise separation losses decrease by increasing thresher speed because more threshing and separation is done in the threshing unit. This removes load from the separator.

Such conflicting relations can be found for all of the settings. For further explanations on the other correlations, see [72].

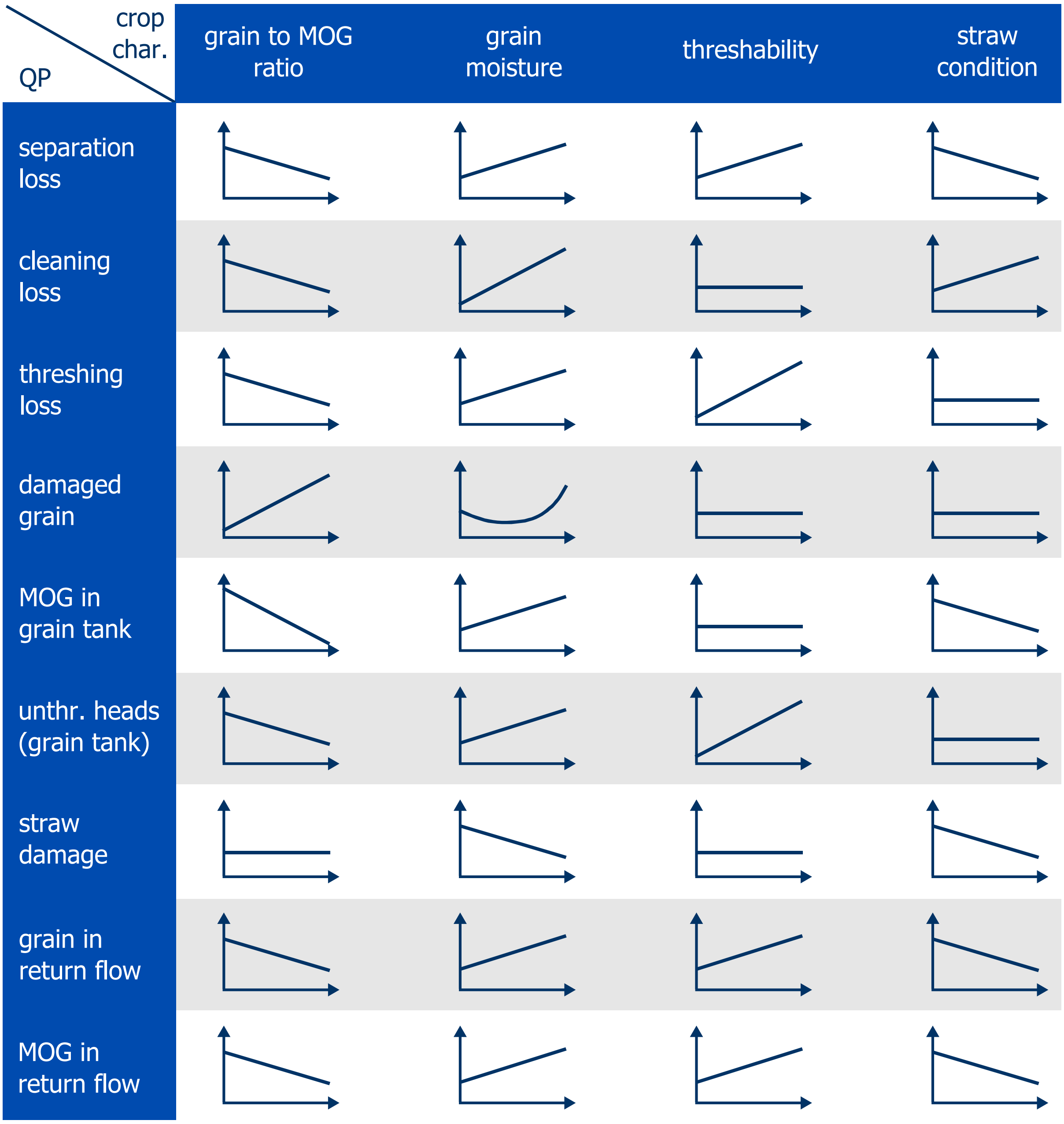



*Figure (3.4)* Correlations between crop characteristics and process parameters.

The influence of crop properties on the main process parameters is shown in figure 3.4. The grain to MOG ratio is the total mass of grain in relation to the total mass of MOG of the plant as it is cut by the header. The grain to MOG ratio depends on the crop type and variety. Fertilizers also have an impact on this parameter. During harvest the grain to MOG ratio of the material that enters the combine can be influenced by the cutting height. Grain moisture is the mass percentage of water in relation to the overall grain weight. There exists a correlation between the air humidity and grain moisture. The grain moisture also depends on the crop type. It can be influenced indirectly by the choice of the harvest time. The crop properties threshability and straw condition are qualitative parameters. Threshability describes how easily the grain can be removed from the ear. The verbal grading is shown in figure 3.5. The straw condition describes if the straw is brittle, normal or tough.

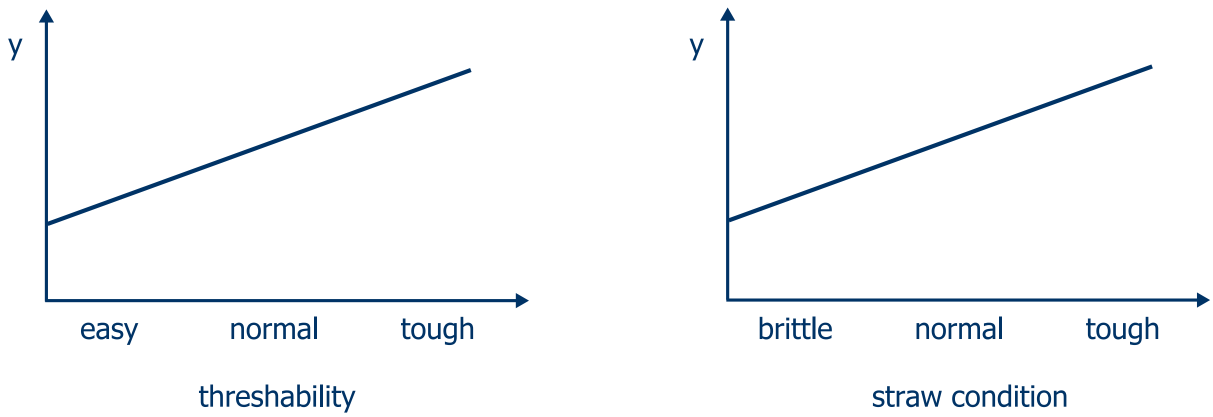



*Figure (3.5)* Qualitative values of the crop properties threshability and straw condition.

The grain to MOG ratio influences the dampening in the threshing unit and the total amount of separated MOG particles. The lower the grain to MOG ratio, the higher the dampening and the less grain is detached from the ears in the threshing unit. This leads to an increase in threshing loss and unthreshed heads in the grain tank. On the other hand, a high dampening reduces the amount of broken grain. Often the settings of the threshing unit are chosen more aggressive because of the higher dampening when the grain to MOG ratio is low. Thus, the more MOG particles are separated. Due to the higher amount of MOG particles, the fluidization of the material mat in the cleaning unit is impeded. Less MOG particles are blown out. This leads to an increased amount of MOG in the grain tank and the return flow. The higher the grain to MOG ratio, the more difficult it is for the grain to penetrate the straw mat in the separator and cleaning unit. This leads to an increase in separation loss, cleaning loss and grain in return flow.

The higher the grain moisture, the more difficult it is to detach the grain from the ear. This means an increase in threshing loss and unthreshed heads in the grain tank. Grain damage is also influenced by grain moisture. There is an optimum grain moisture at which elasticity and strength of the grain are appropriate to endure the strikes of the threshing elements. At low moisture the grain is brittle and cracks easily, at high moisture the grain's strength is too low and kernels get smashed. Separation and cleaning loss, grain in the return flow and straw damage are rather a function of straw moisture than of grain moisture. However, there is a correlation between grain and straw moisture. The higher the grain moisture, the higher the straw moisture. Friction between particles increases with higher straw moisture which makes separation of grain more difficult. This is the reason why separation losses, cleaning losses and the amount of grain in the return flow increase. At higher straw moisture, the straw is tougher and is less damaged.

Regarding threshing condition and straw condition there are no conflicting relations. The easier the grain is to thresh and the tougher the straw, the better it is for the process parameters. For most of the process parameters a low grain to MOG ratio is desirable. The only exception is grain damage. Grain is damaged easily without a sufficiently damping straw mat. Low grain moisture is desirable for most of the process parameters. Here again, grain damage is an exception. There is an optimum moisture at which the lowest grain damage occurs. Regarding straw damage, a higher straw moisture leads to less straw damage.

The explanations in section 3.3 are part of the knowledge about combine processes that is available at the Chair of Agricultural Systems and Technology at TU Dresden. The major part of this knowledge has not been documented before. Section 3.3 is mainly the result of several internal conversations.

## 3.4 Discussion

A considerable number of models has been developed over the past decades. These models comprise immense knowledge and they show once again the extent and the complexity of the threshing and separation processes in a combine harvester. However, a model that can serve as a basis for a control system for process optimization has the following requirements:

1. All parameters that determine harvest quality have to be represented as model outputs.
2. All relevant combine settings have to be represented explicitly.
3. All model parameters have to be known.

Of the above described models hardly any model contains combine settings explicitly. Many models focus on particular functions of the combine harvester. Most of the models have abstract model parameters that have to be derived by regression analysis on experimental data. The model parameters have to be adjusted to different crop and combine types. A universal deterministic mathematical model that is able to quantify harvest quality and the combine performance has not yet been developed. As the literature research has shown, the development of models for threshing and separation processes is in general time consuming. It is also obvious that an analytical model on combine processes will always contain a set of abstract model parameters that incorporate the impacts of a variety of influencing parameters. Online process identification is the only method to automatically adjust abstract model parameters to existing conditions. Within this work, these efforts are considered as too time consuming.

> An alternative is to use the comprehensive qualitative model given by [71, 72]. The model consists of direct correlations between all relevant combine settings and all crucial quality parameters. This model (see figure 3.3) is the only one that is relevant for the development of a control system with feasible effort and within feasible time. As the model does not contain a problem oriented representation, there is the need to enhance the model by existing expert knowledge on process optimization. When an expert optimizes the harvest quality, he applies a sequence of setting adjustments, starting with the setting that seems to be most promising. The existing model (figure 3.3) does not contain such sequences.

An overview of optimization methods is given in the next chapters. The purpose is to identify optimization methods that are capable to deal with qualitative knowledge and that best fit to the characteristics of the given control objective, the optimization of the threshing and separation process in the combine harvester. The characteristics of expert systems and the procedure of knowledge acquisition are described in section 4.2.3.

# 4 Evaluation and selection of methods for solving optimization problems

## 4.1 Analytical optimization methods

### 4.1.1 Introduction to optimization

Optimization means finding the best, or optimal, solution to a problem. The mathematical expression of an optimization problem is: Find the minimum or maximum of a function $f$ by varying the decision variables of this function. It depends on the optimization problem if the optimal solution is the minimum or the maximum of the given function. The function $f$ is also referred to as the objective function, the cost function, utility function or fitness function [73, 74].

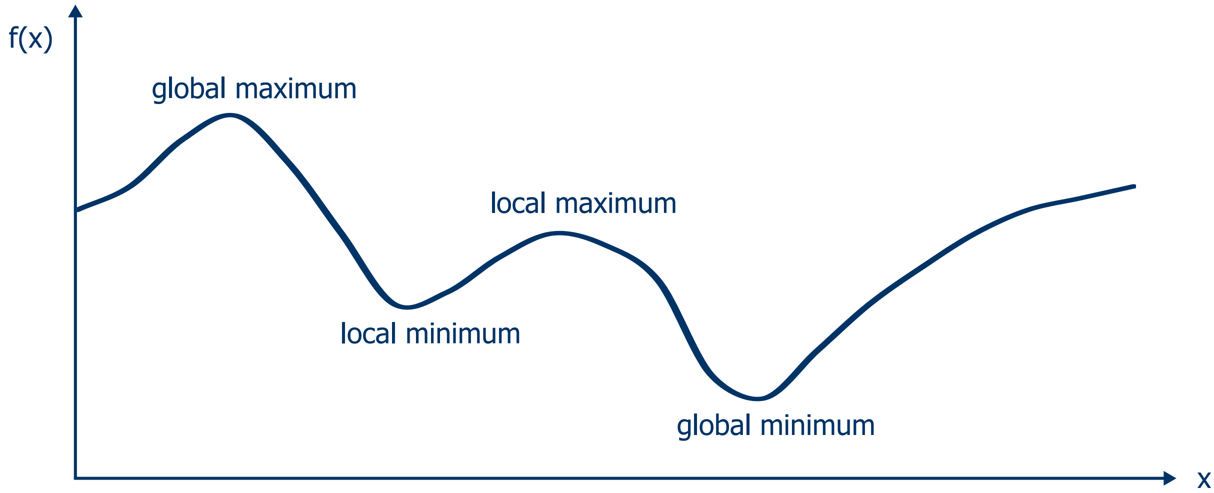



*Figure (4.1)* Global and local minima and maxima of a function $f(x)$.

A function can have global and local maxima and minima. Local minima and maxima are also referred to as relative minima and maxima. Global minima and maxima are referred to as absolute minima and maxima. Figure 4.1 shows an example with a one-dimensional function $f(x)$. The definitions for global and local minima and maxima are given below. The value $x^*$ is referred to as the optimal point (either the minimum or the maximum) [73, 75, 76, 77].

*Table (4.1)* Definitions for global and local minima and maxima.

| name | definition |
|---|---|
| local minimum | $f(x^*) < f(x)$ in a $x^*$- neighborhood |
| local maximum | $f(x^*) > f(x)$ in a $x^*$- neighborhood |
| global minimum | $f(x^*) < f(x)$ for all $x$ in the search space |
| global maximum | $f(x^*) > f(x)$ for all $x$ in the search space |

The simplest optimization problem is shown in figure 4.1: finding the minimum or maximum of a function with one decision variable $f(x)$. In more complex optimization problems, the objective function depends on several independent decision variables. This case is called multi-dimensional optimization problem. The most complex case is multi-objective optimization. There are several objective functions which have to be optimized at the same time. The mathematical formulations for these three categories of optimization problems is given in figure 4.2.

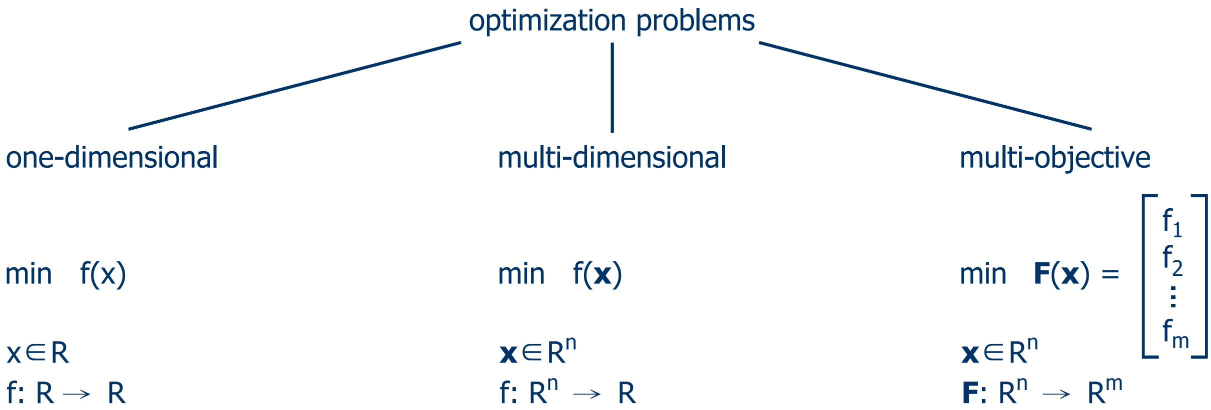



*Figure (4.2)* Different categories of optimization problems according to their dimension.

A different type of optimization problem is one that is subject to constraints. Table 4.2 gives an overview of constrained and unconstrained optimization problems for the multi-dimensional case:

$$min\ f(\boldsymbol{x}),\ \boldsymbol{x} \epsilon R^n$$

Constraints can also be applied in the one-dimensional and the multi-objective case.

*Table (4.2)* Constrained and unconstrained optimization problems [77, 76, 75].

| optimization problem | constraints | mathematical formulation |
|---|---|---|
| unconstrained | none | |
| linearly constrained | equality constraint<br>inequality constraint | $A_1\boldsymbol{x} = \boldsymbol{b}_1$<br>$A_2\boldsymbol{x} \geq \boldsymbol{b}_2$ |
| nonlinearly constrained | equality constraint<br>inequality constraint | $c_i(\boldsymbol{x}) = 0,\ i = 1, ...m'$<br>$c_i(\boldsymbol{x}) \geq 0,\ i = m'+1, ..., m$ |

In the simplest case an optimization problem can be solved analytically by determining the zeros of the first derivative of the objective function. Numerical methods are applied if one of the following conditions are true:

- an analytical description of the objective function $f$ does not exist,
- the first derivative $f'$ cannot be determined analytically,
- the optimality conditions (second derivative $f''$) cannot be checked analytically.

There exist a large number of numerical methods for each class of optimization problem. An overview of selected methods is given in the following sections. The common principle is that they iteratively search for the optimal value [78].

### 4.1.2 One-dimensional optimization methods

A one-dimensional minimization problem is stated as follows:

$$\begin{aligned} min \quad & f(x) \\ x \quad & \in \quad R \\ f: R \quad & \rightarrow \quad R \end{aligned}$$

In the following we refer to a minimization problem. The presented algorithms are also applicable for maximization problems. A maximization problem is equal to minimizing the negative value of the objective function.

The first method that is suitable to solve one-dimensional optimization problems is the Golden Section search. Golden Section search is an interval reduction procedure. It is based on the assumption that the function $f$ is uni-modal in the search interval [a,b], which means that $f$ has only one local minimum. Interval reduction procedures only require function values but do not need the derivatives of the function. The second and the third method that will be presented are based on polynomial interpolation. They both require derivatives.

### Golden Section search

The Golden Section search is based on an iterative reduction of the search interval [a,b] by a constant contraction factor 1:c. At each iteration two interior points are compared with each other. The interior points are chosen in a way that the reduction of the search interval is symmetric:

$$x_1 - a = b - x_2 = (1-c)(b-a) \tag{4.1}$$

$$0.5 \leq c \leq 1 \tag{4.2}$$

The interior points are determined according to the following equations:

$$x_1 = a + (1-c)(b-a) \tag{4.3}$$

$$x_2 = a + c(b-a) \tag{4.4}$$

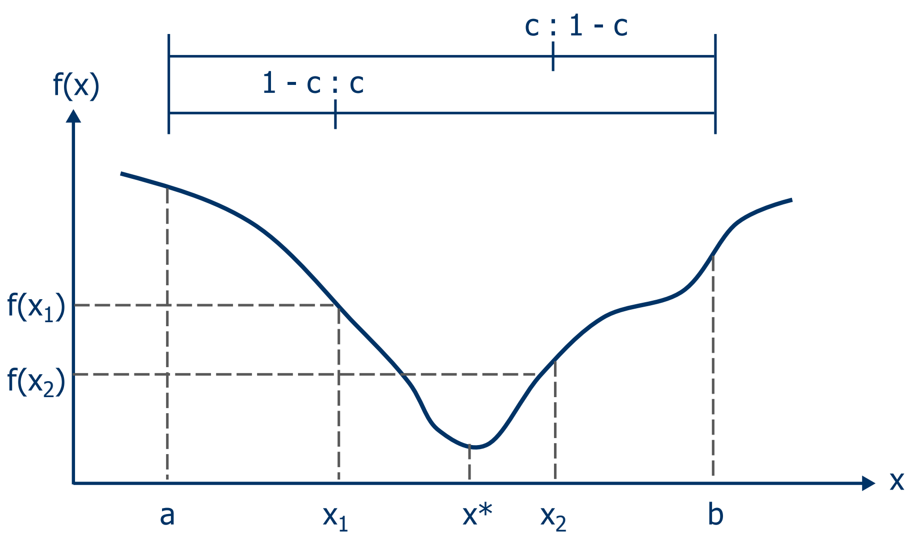



*Figure (4.3)* Golden Section intervals.

Then the function values at these points are compared with each other. If $f(x_1) < f(x_2)$, then the optimum must lie in the range $[a, x_2]$. If $f(x_1) \geq f(x_2)$, the optimum lies in the range $[x_1, b]$ (figure 4.3). In each iteration, two new interior points $x_1$, $x_2$ are determined and their function values are evaluated. The procedure is repeated until the optimal value $x^*$ is determined with sufficient accuracy, meaning that the search interval is small enough. The goal is to minimize the number of objective function evaluations. By setting the contraction factor to

$$c = \frac{\sqrt{5}-1}{2} \approx 0.618,$$

only one function evaluation per iteration is necessary. The resulting algorithm is shown in figure 4.4. The Golden Section algorithm guarantees convergence but is relatively slow because it does not use information about the slope of the function [76, 77, 78].

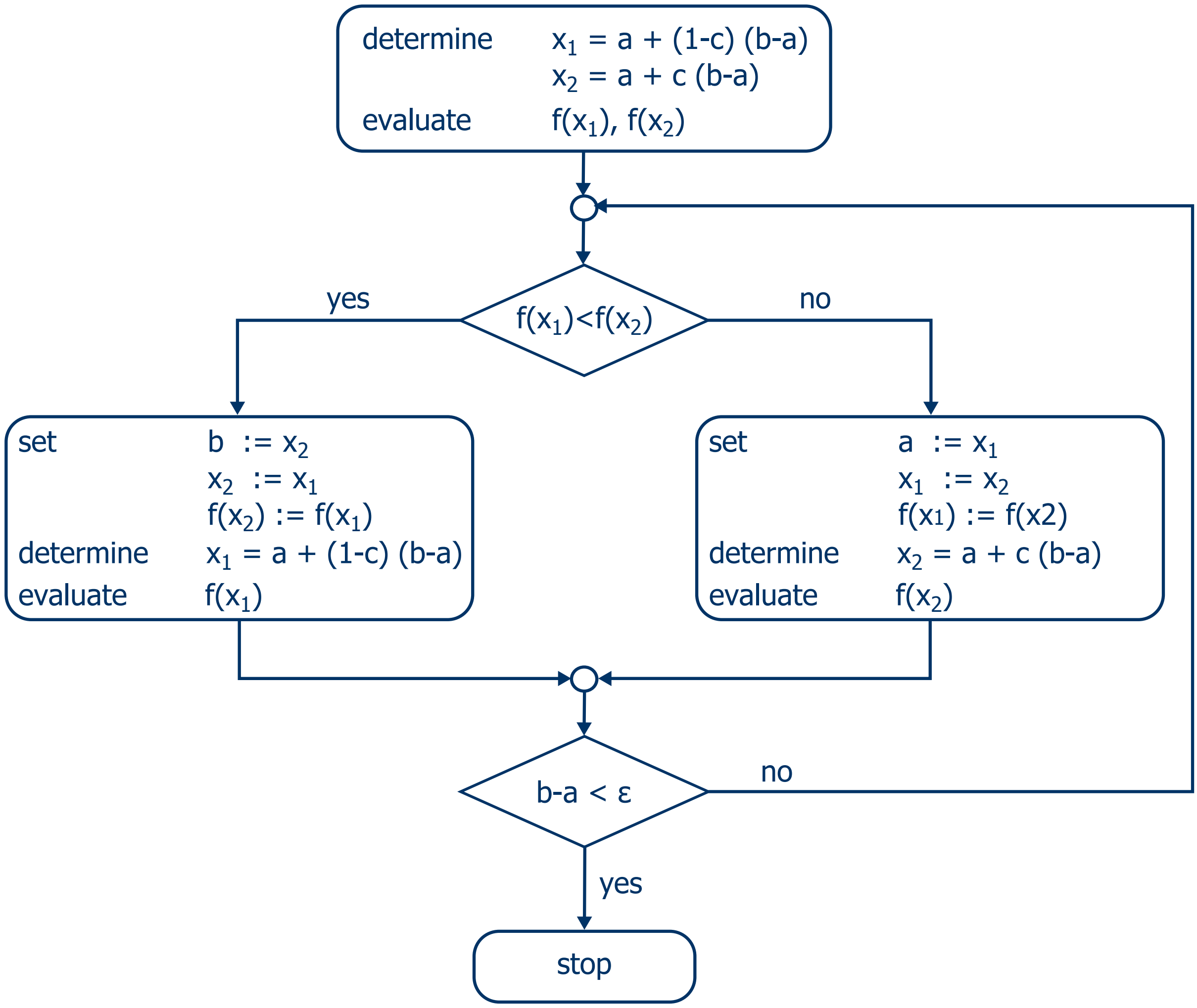



*Figure (4.4)* Golden Section algorithm according to [78].

The Fibonacci search is related to the Golden Section algorithm. In contrast to the Golden Section search, it uses a dynamic contraction factor [76, 77].

### Newton's method

The idea of Newton's methods is to fit a quadratic function $q$ through the current point $x_k$. The first and second derivatives of the approximation function $q$ matches the first and second derivative of the original function $f$ at the point $x_k$:

$$\begin{aligned} q(x_k) &= f(x_k) & (4.5) \\ q'(x_k) &= f'(x_k) & (4.6) \\ q''(x_k) &= f''(x_k) & (4.7) \end{aligned}$$

The approximation function is of the form

$$q(x) = f(x_k) + f'(x_k)(x - x_k) + \frac{1}{2}f''(x_k)(x - x_k)^2. \tag{4.8}$$

The function $q$ is minimized instead of the original function $f$. By setting the first derivative of the approximation to zero

$$q'(x) = f'(x_k) + f''(x_k)(x - x_k) = 0, \tag{4.9}$$

one obtains the iterative algorithm

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)}. \tag{4.10}$$

Newton's method uses the slope of the objective function to determine the next iteration point [76, 77].

### Secant method

A disadvantage of Newton's method is that it requires the first and second derivatives of the objective function. In the Secant method, the second derivative is replaced by the approximation

$$f''(x_k) \approx \frac{f'(x_k) - f'(x_{k-1})}{x_k - x_{k-1}}, \tag{4.11}$$

thus

$$x_{k+1} = x_k - \frac{x_k - x_{k-1}}{f'(x_k) - f'(x_{k-1})} f'(x_k). \tag{4.12}$$

The Secant method uses the secant between the $(k-1)$-th and the $k$-th points to determine the $(k+1)$-th point [77].

### 4.1.3 Multi-dimensional optimization methods

In a multi-dimensional optimization problem a function of several independent variables has to be optimized. The mathematical formulation is as follows:

$$\begin{aligned} min \quad & f(\boldsymbol{x}), \\ \boldsymbol{x} \quad & \in \quad R^n \\ f : R^n \quad & \to \quad R \end{aligned}$$

Generally, there exist two different types of multi-dimensional optimization algorithms: direct search algorithms and gradient-based algorithms. Direct search algorithms are based on the evaluation of the objective function. Derivatives are not required. One method among direct search algorithms is the simplex method. If there are $n$ independent variables, a polyhedron of $n+1$ points is composed. The $n+1$ points form the vertices of the polyhedron. In each iteration the loss function values at the vertices are compared. Based on the comparison of the function values, the new search direction is computed. The polyhedron is then moved towards the promising region. There are various possibilities how to define the shape and the size of the polyhedron. The method is computationally expensive if all vertices are recomputed [79].

Gradient-based algorithms require derivatives. The general algorithmic structure of gradient-based algorithms is as follows:

1. A starting point $x_o$ is selected.
2. A search direction $\boldsymbol{s}_k$ is determined, with $\boldsymbol{s}_k \in R^n$ and $\|\boldsymbol{s}_k\| = 1$. If one is searching for a minimum, the vector $\boldsymbol{s}$ is of descending direction. If one is searching for a maximum, $\boldsymbol{s}$ is of ascending direction.
3. The value for the scalar step size $\alpha_k > 0$ is determined.
4. The next iteration point is determined according to the following equation:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \alpha_k \boldsymbol{s}_k.$$

5. Check the stop condition. If it is true, then stop, otherwise continue at step 2. The stop condition can have different forms:

$$\begin{aligned} 0 \leq \quad & f(\boldsymbol{x}_k) - f(\boldsymbol{x}_{k-1}) && \leq \varepsilon_a \\ & \left| \frac{df(\boldsymbol{x})}{d\boldsymbol{x}}_{|\boldsymbol{x}=\boldsymbol{x}_{k+1}} \right| && \leq \varepsilon_b \\ |\boldsymbol{x}_{k-1} - \boldsymbol{x}_k| \leq \quad & |\alpha_k| && \leq \varepsilon_c \end{aligned}$$

For the determination of the search direction $\boldsymbol{s}_k$ and the step size $\alpha_k$, there exist different possibilities. For further reading see [73, 75, 77, 78].

### 4.1.4 Multi-objective optimization

In many applications, there is more than one objective to be optimized at the same time. Problems with multiple objectives are called multi-objective, multi-criteria or vector optimization problems. The formal definition of a multi-objective optimization problem is stated as follows:

$$min\ \boldsymbol{F}(\boldsymbol{x}) = \begin{bmatrix} f_1(\boldsymbol{x}) \\ f_2(\boldsymbol{x}) \\ \vdots \\ f_m(\boldsymbol{x}) \end{bmatrix} \tag{4.13}$$

$$\boldsymbol{x} \in R^n \tag{4.14}$$

$$\boldsymbol{F} : R^n \rightarrow R^m \tag{4.15}$$

$\boldsymbol{F}$ is the vector of objectives to be minimized. The search space is also called parameter space or decision space. In general, there are three different types of multi-objective optimization problems:

- minimize all the objective functions,
- maximize all the objective functions,
- minimize some objective functions and maximize the others.

All of these types can be converted into an equivalent minimization problem as stated in equation 4.13.

The objectives are normally in conflict with each other. Hence, a vector of decision variables $\boldsymbol{x}^* = [x_1, x_2, \ldots, x_n]^T$ that minimizes each objective function is an utopian solution. A conflict between the objectives exists if improvement in one objective leads to deterioration in at least one other objective. In multi-objective optimization problems, the goal is to find good compromises between the objectives. Such compromises are called Pareto optimal solutions. A solution is Pareto optimal if it is not possible to improve a given objective without deteriorating at least another objective. In other words, a solution is Pareto optimal if there exists no other solution that gives improved performance with regard to all objectives. The formal definition is as follows [77]:

A decision variable $\boldsymbol{x}^* \in \Omega$ is called a Pareto optimal solution if there exists no $\boldsymbol{x} \in \Omega$ such that for $i = 1, 2, ..., n$

$$f_i(\boldsymbol{x}) \leq f_i(\boldsymbol{x}^*)$$

and for at least one $i$

$$f_i(\boldsymbol{x}) < f_i(\boldsymbol{x}^*).$$

$\Omega$ is the allowed search space of decision variables. Multi-objective optimization problems do not have a single, unique solution as in single-objective optimization problems, but a set of optimal solutions, defined as the Pareto optimal set. The Pareto optimal set is the set of solutions $\{\boldsymbol{x}_1^*, \boldsymbol{x}_2^*, ...\}$ that represents the compromise solutions between the different conflicting objectives. The corresponding objective function values are called the Pareto front. The size of the Pareto optimal set increases according to the number of objectives. Figure 4.5 illustrates the Pareto front for a two-dimensional optimization problem [74].

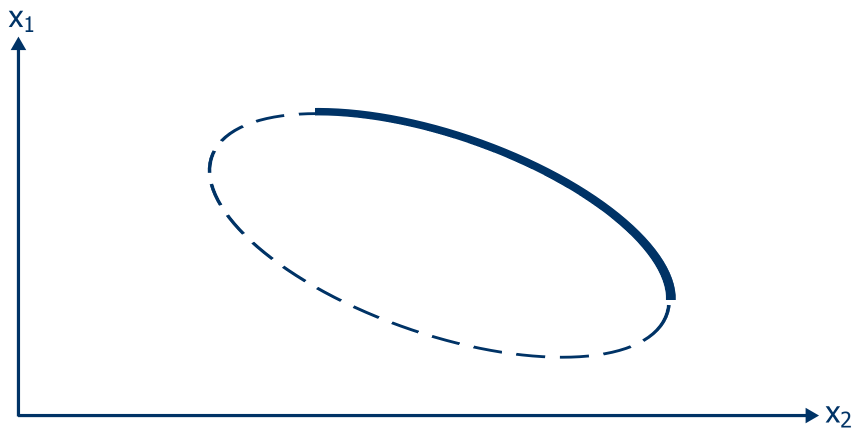



*Figure (4.5)* Example of a Pareto front.

There exist no standard optimization methods for multi-objective optimization problems. Multi-objective optimization problems are solved by transforming them into a single-objective optimization problem. Different possible transformation methods are listed in table 4.3 [74, 77, 80].

After transforming the multi-objective optimization problem into a single-objective optimization problem, the optimization methods described in section 4.1.3 can be applied.

*Table (4.3)* Methods for transforming a multi-objective optimization problem into a single-objective optimization problem.

| method | description |
|---|---|
| Aggregation method/ weighted method/ weighted-sum method | ∘ take a linear combination of the components of the objective function vector: $f(\boldsymbol{x}) = \boldsymbol{c}^T \boldsymbol{F}(\boldsymbol{x}),\ c_i > 0$<br>∘ normalize the objectives if they are not in the same scale: $f_{i-norm} = \frac{f_i - f_{i\ min}}{f_{i\ max} - f_{i\ min}}$ |
| Minmax method | ∘ take the maximum of the components of the objective vector: $f(x) = max(f_1(x), f_2(x), ..., f_l(x))$<br>∘ can only be applied if the objective functions are in the same unit |
| p-norm | ∘ take the p-norm of the objective vector: $f(\boldsymbol{x}) = \parallel \boldsymbol{F}(\boldsymbol{x}) \parallel_p$<br>∘ the components of the objective function vector must be non negative |
| Weighted metrics | ∘ a reference point $\boldsymbol{z} = [z_1, z_2, ..., z_l]$ is defined (defines the aspiration level/ goal)<br>∘ the distance metric between the reference point $\boldsymbol{z}$ and the objective function is minimized: $min(\sum_{j=1}^{l} \lambda_j \lvert f_i(x) - z_j \rvert^p)^{1/p},\ 1 < p < \infty$ |
| Constraint method | ∘ optimize one selected objective $f_k$ subject to constraints on the other objectives, e.g.: $min\ f_1(x),\ subject\ to\ \begin{array}{ll} f_2(x) & \leq b_2 \\ \vdots & \\ f_l(x) & \leq b_l \end{array}$<br>∘ $b_2, ..., b_l$ are given constraints that represent an upper bound for the objectives |
| Sequential method | ∘ carry out the search according to a given preference order (significance) of the objectives<br>∘ a set of single-objective problems is solved sequentially |

### 4.1.5 Conclusions

Optimization means finding the best, or optimal, solution to a problem. There are numerous methods which guarantee the detection of a local optimum. However, it depends strongly on the objective function if a global optimum can be found. For the given optimization problem - optimizing combine processes - there exists no analytical objective function (no comprehensive analytical model). Hence, optimization methods that use derivatives can not be applied. Interval reduction algorithms (e.g. Golden Section search) and direct search algorithms (e.g. simplex method) are the only relevant optimization methods. The Golden Section algorithm does not even require absolute function values. However, this algorithm is only applicable for one-dimensional optimization problems. The simplex method is based on the comparison of several function values in each iteration. For the given optimization problem, $n + 1 = 7$ function values have to be compared. In the interactive operating mode, the operator would have to do this evaluation. This would mean that the operator has to modify the combine settings 7 times, memorize the 8 quality parameters for each of the 7 combinations of combine settings and then make a comparison. This is simply impossible. The simplex method is therefore not relevant for the given optimization problem. All of the transformation methods in table 4.3 can be applied for the given optimization problem if function values are available. This is only the case in the automatic operating mode. Here, sensors provide absolute function values for the quality parameters. In the interactive operating mode, only relative evaluation (“worse”, “same”, “better”) will be provided by the operator.

The Golden Section algorithm is relevant for the given optimization problem because it does not require absolute function values. The Golden section search is applied for one-dimensional optimization problems. Alternative optimization methods that handle multi-dimensional and multi-objective optimization problems have to be found. An alternative to analytical optimization methods are methods of Artificial Intelligence. An overview of this domain is given in the next chapter.

## 4.2 Methods of artificial intelligence

### 4.2.1 Introduction

The field of Artificial Intelligence (AI) is a rather young field which started in the first half of the 20th century. The original focus of AI was an artificial general intelligence. The goal was to build software programs that can solve a variety of complex problems in different domains. The vision was that these software programs are able to learn from experiences and to adjust autonomously to changing environments, the same as an intelligent human being does. However, this approach was not successful. Since the 1980s there has been a rapid growth in AI methods that solve problems in clearly defined specific domains. Nowadays, a considerable number of diverse AI methods is available that is suitable for a variety of applications. An overview of applications is given in table 4.4.

*Table (4.4)* Sample applications of methods of Artificial Intelligence [81].

| application | example |
|---|---|
| interpretation | derive a description of a situation from sensor data |
| prediction | derive possible consequences of a given situation |
| diagnosis | determine the cause of a failure |
| design | configure objects that are subject to specific requirements |
| planning | create a sequence of actions to reach a goal |
| monitoring | detect failures by comparison of real and supposed behavior |
| control | determine values for actuating variables |
| classification | classify objects into groups with similar characteristics |
| optimization | find a solution that minimizes a given objective function |

There is no standard definition of what AI is. There is even no unique definition of intelligence. Several possible definitions for intelligence are taken from [82]. “Intelligence is the

- ... capacity to acquire and apply knowledge in a variety of domains.”
- ... ability to achieve complex goals in complex environments.”
- ... ability to work and adapt to the environment with insufficient knowledge and resources.”

Artificial Intelligence can be defined as a sub domain of computer science that aims to automate intelligent behavior, such as reasoning and learning. The two most fundamental fields of AI are [83]:

1. knowledge representation (capture in a language the full range of knowledge required for solving a problem), and
2. algorithms needed to apply that knowledge.

Methods and applications that do not belong to AI are for example pure numeric computations such as solving a system of linear equations, numeric differentiation and integration, and statistical analysis [84]. AI methods are applied in problem domains that rather require qualitative reasoning and where efficient exact algorithms to solve the problem are not available. Further characteristics of problems where AI methods are suitable are listed below [85, 86, 87, 88]:

- Reasoning for problem solving is based on knowledge.
- Procedures for problem solving are heuristic or approximate.
- The knowledge is uncertain, inexact or incomplete.
- Comprehensive analytical models for the technical process are not available.
- Finding an optimal or exact solution to the problem is either too expensive or not possible, however, a "sufficient" solution can be found.

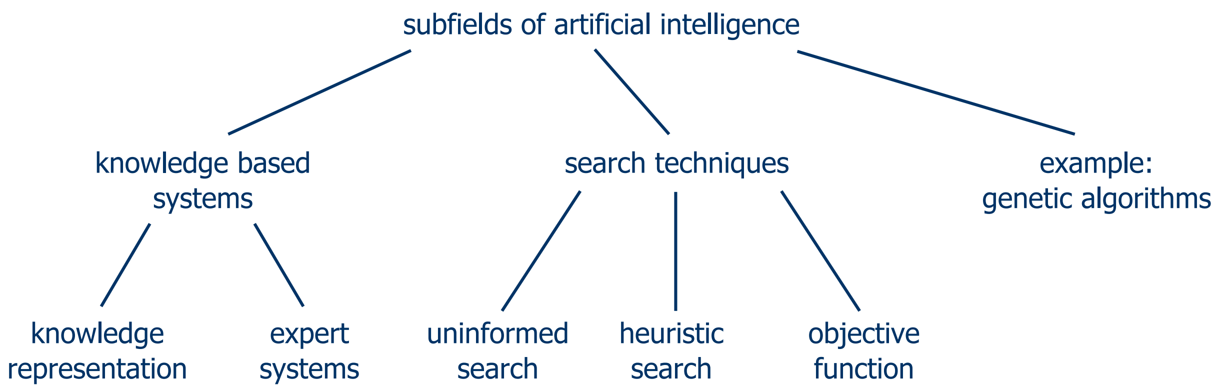



*Figure (4.6)* Overview of AI sub fields that are treated in the following sections.

Figure 4.6 gives an overview of the AI sub fields that are relevant for the given problem of optimizing combine processes. Genetic algorithms (GA) are used as an example because GAs incorporate many of the features that are characteristic for AI methods.

## 4.2.2 Knowledge representation

### 4.2.2.1 General

The differentiation of the term knowledge from data and information is shown in figure 4.7. The presence of a context transforms data into information. Knowledge is the application of information.

Knowledge can be represented in form of facts of rules (IF conditions, THEN action(s)/ conclusion(s) ), in form of models (differential equations, Bayesian networks, ...) or in form of problem-solution pairs. The latter is called a case-based system. Solutions to previous problems are memorized and applied to similar new problems [90].

The characteristics of the relevant knowledge have to be respected when choosing a knowledge representation. Knowledge can have the different characteristics shown in table 4.5 [91, 92, 93, 94].

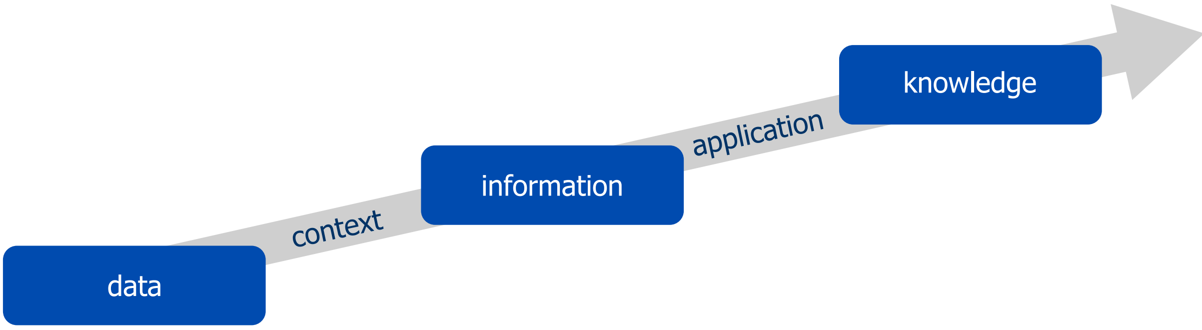



*Figure (4.7)* Data - information - knowledge hierarchy [89] .

*Table (4.5)* Different characteristics of knowledge.

| characteristic | description |
|---|---|
| incomplete | important knowledge for decision making is missing |
| inconsistent | contradictions in the knowledge base |
| uncertain | characterized by a probability $<1$ for the truth of a statement |
| vague | usage of imprecise expressions like “large” or “small” |

#### 4.2.2.2 Representing uncertain knowledge

**Certainty factor** The certainty factor method is an intuitive method for handling uncertainty. Experts can rate their confidence in facts, events or rules which are not known as definitely true of definitely false. The certainty factor (CF) is defined in the range:

$$CF \in [-1, 1] \tag{4.16}$$

where the value $-1$ means that the fact, event or rule is definitely false, $+1$ that it is definitely true and $0$ that there is complete ignorance if the fact, event or rule is true or false. Often, the ratings of facts, events or rules is based on a certain background knowledge, called evidence (E). This is written as:

$$CF(A|E) = x \tag{4.17}$$

where $A$ is a fact or rule, $E$ is the evidence for this fact/ event/ rule and $x$ is any number between -1 and 1. For example

$$CF(hot\ temperatures \mid sun\ is\ shining) = 0.7 \tag{4.18}$$

says that the confidence that there are hot temperatures when the sun is shining is 0.7.

The certainty factor is a relative measure for uncertainty, in contrast to absolute measures for uncertainty like a probability assignment. The certainty factor can not be treated as a probability because it does not satisfy the additivity axiom. The additivity axiom says that the probabilities of the set of mutually exclusive facts or events have to sum to one [83, 86, 95, 96].

**Bayesian networks** Another possibility for modeling uncertainty is the Bayesian probability. The causal relationships between variables can be modeled as a Bayesian network. A Bayesian network is a graph that contains nodes and arrows between nodes. The nodes correspond to the variables, the arrows describe direct relationships between variables. The quantity of the dependencies between variables is expressed by conditional probabilities.


*Figure (4.8)* Example of a simple Bayesian network.

Figure 4.8 shows an example of a Bayesian network with the two variables ’skiing accident’ and ’broken leg’. Let $P(skiing\ accident) = 0.03$ be the prior (or marginal) probability that a person has a skiing accident and let $P(broken\ leg) = 0.01$ the prior probability that a person has a broken leg. Let’s say that the likelihood to break a leg in a skiing accident is $P(broken\ leg|skiing\ accident) = 0.2$.

With the Bayesian rule of conditioning one can determine the probability that a person had a skiing accident when there is evidence that he/ she has a broken leg:

$$P(A|E) = \frac{P(E|A) \cdot P(A)}{P(E)} \tag{4.19}$$

With A = skiing accident and E = broken leg, it is:

$$P(skiing\ accident|broken\ leg) = \frac{0.2 \cdot 0.03}{0.01} = 0.6$$

Two important characteristics of the utilized probabilities are:

$$\begin{aligned} 0 \leq P(A|E) &\leq 1 \\ P(A|E) + P(\neg A|E) &= 1 \end{aligned}$$

where $\neg A$ is the negation of event A, meaning event A is not true. One commitment of the Bayesian approach for modeling uncertainty is that all the prior probabilities, as well as the relationships between observations and events have to be estimated or empirically determined [97, 98, 99, 100].

**Dempster-Shafer theory of evidence** The Dempster-Shafer theory of evidence is the third possibility to represent uncertainty. The credibility status of a fact or event is represented by an interval

$$[bel(A),\ pl(A)] \tag{4.20}$$

where

$$\begin{aligned} bel(A) &\in [0,1] & (4.21)\\ pl(A) &\in [0,1] & (4.22)\\ bel(A) &\leq pl(A) & (4.23)\\ pl(A) &= 1 - bel(\neg A). & (4.24) \end{aligned}$$

The lower bound of the interval, the belief $bel(A)$, represents the extent to which the fact is definitely supported. The upper bound, the plausibility $pl(A)$, represents the extent to which the evidence fails to refute it. The larger the interval, the bigger is the uncertainty. The interval $[0,1]$ means absolute ignorance about the truth of falsity of a fact. The interval $[1,1]$ means absolute certainty that the fact is true. The additivity axiom is not in general obeyed for belief functions:

$$bel(A) + bel(\neg A) \leq 1 \tag{4.25}$$

Only for precise statements, when the lower and the upper bound of the interval are equal, it is

$$bel(A) + bel(\neg A) = 1. \tag{4.26}$$

Such a belief function is referred to as the Bayesian belief function. In this special case, the belief (or plausibility) is a classical probability [95].

#### 4.2.2.3 Fuzzy systems

Fuzzy logic is the most important method for representing vague knowledge [84]. The key feature of fuzzy logic is a gradual transition between complete membership and complete exclusion of a variable. Thus, fuzzy sets allow partial membership. The partial membership $\mu_A$ of a variable X can take values ranging from 0 to 1:

$$\mu_A : X \rightarrow [0,1] \tag{4.27}$$

The membership function $\mu_A$ can be of any form. Most common are triangular, trapezoidal and bell-shaped membership functions. If the degree of membership of variable X to a set A is 0 ($\mu_A = 0$), then X is definitely not a member of the set A. If the degree of membership is 1 ($\mu_A = 1$), then X is a complete member of the set A. Any degree of membership in between 0 and 1 represents partial membership.

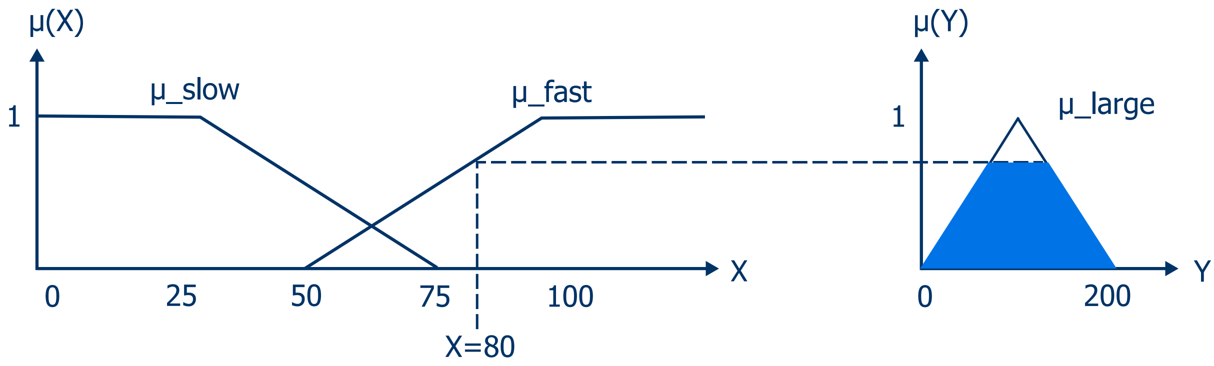



*Figure (4.9)* Example of membership functions for fuzzy variables X and Y.

Fuzzy logic can be used, for example, when rules of a knowledge based system use vague variables like "fast", "slow", "high", and so on. An example could be:

*"If the speed of your car is fast, then keep a large distance to the car in front of you."*

The terms "fast" and "large" are vague, linguistic variables. In order to apply the above rule, the sensor value from the speed sensor of your car has to be transformed into the linguistic variable for speed ("slow", "fast"), which is used in the precondition of the above rule. This process is called fuzzification. In the example in figure 4.9 the speed X=80 km/h has an associated degree of membership to the set "FAST" of about $\mu_{fast} = 0.7$. This degree of membership is applied to the output variable Y of the system, the variable "distance" in the conclusion of the above rule:

$$\mu_{fast}(x) = \mu_{large}(y) \tag{4.28}$$

A next step, called defuzzification, transforms the degree of membership of variable Y to the set "LARGE" into a numerical value for the variable Y (distance). A common method for defuzzification is to calculate the central of the filled area under the membership function $\mu(Y)$ (figure 4.9) [101, 102, 103, 84, 104].

Fuzzy models for the MOG content in the grain tank of a combine harvester and for sieve losses can be found in [64, 65]. Calibration data is required to determine the model parameters. Hence, the usage of the model for online prediction while harvesting is not possible. Only qualitative usage is possible. However, for qualitative knowledge, there are simpler forms of knowledge representation (see section 3.3). Fuzzy controllers for the cleaning process and as a loss controller are described in [56] and

[105]. Although the rule sets might be valid generally, the fuzzy membership functions must be tailored to the combine type, the crop type and the region (in the world). Optimization and maintenance of the controller are a challenge.

### 4.2.3 Expert systems

#### 4.2.3.1 Introduction

Expert systems are a sub domain of knowledge based systems. Knowledge based systems require a large amount of domain-specific knowledge. The collection of knowledge is called the knowledge base. The knowledge base contains both domain-specific heuristic knowledge (e.g. rules of thumb) and algorithmic knowledge. In knowledge based systems mathematical as well as symbolic reasoning techniques are used. A system is called an expert system if it reproduces the knowledge and the capability to draw conclusions of qualified experts in a narrowly defined domain. It reproduces problem solving strategies of human experts to solve a problem or make a decision. Expert systems simulate human reasoning about a problem domain. They don't simulate the domain itself. A crucial feature of expert systems is the capability not only to solve a problem but to explain the solution. An expert system can be regarded as being a storage device for knowledge. By distributing knowledge it can support less qualified users to become experts themselves. Beside being a storage device, an expert system is used for experimental verification of its own knowledge [89, 106, 107, 86, 81, 88, 87].

#### 4.2.3.2 The nature of expertise

A person is called an expert if he is qualified and experienced on a well-defined domain. An expert deals with complex and poorly structured problems and vague knowledge. The special knowledge that goes beyond knowledge being available in literature, and hence being open to the public, is called expertise. Expertise means knowledge and experiences obtained in practice. The nature of expertise incorporates the following features [106]:

1. solve the problem,
2. explain the problem (explain the result),
3. learn anything new about the domain,
4. restructure knowledge,
5. break rules (apply exceptions to rules),
6. determine relevance (realize that a problem is outside of one's sphere of expertise), and

7. degrade gracefully (solve problems that are at the boundaries of one's expertise).

Expert systems are able to perform the first issue. However, it is not clear whether computer systems are capable of sufficiently simulating the other mentioned procedures of human expertise.

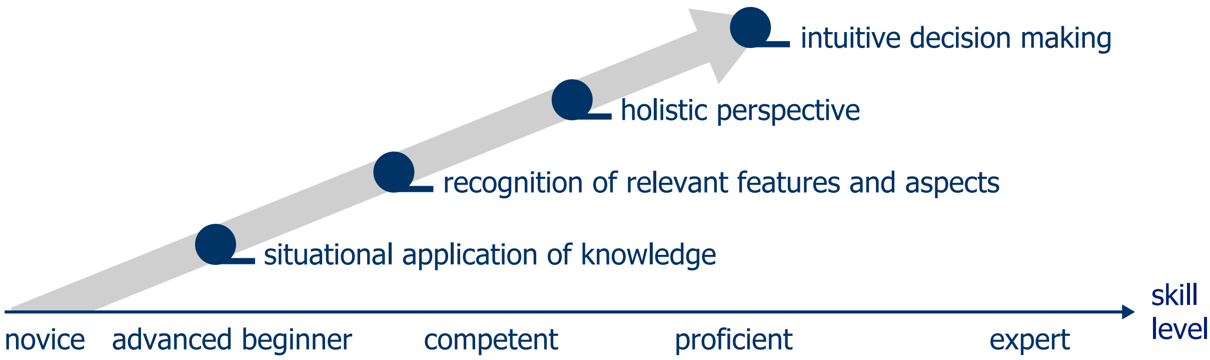



*Figure (4.10)* DREYFUS model of skill acquisition [108, 109, 110] .

Figure 4.10 illustrates the DREYFUS model of skill acquisition. The first stage is the novice. He is able to apply knowledge - e.g. in the form of static rules - without reference to the context. The second state is the advanced beginner. He is able to determine which knowledge - e.g. which rules - are relevant for the given situation. However, he does not recognize which features and aspects of the given situation are relevant. An advanced beginner takes into account the complete number of features and aspects for decision making. The next stage, the competent, performs decision making by examining only the small set of features and aspects that are relevant. A proficient person does not reflect on problematic situations as a detached observer any more, but holistically analyzes the situation. He generates several alternative solutions from which he can select. A proficient analyzes the situation and is therefore aware of facts. In the last stage, an expert simply knows what to do without consciously applying rules. He is often neither aware of facts he takes into account for decision making nor of his actions. Due to this characteristic an expert often has difficulties in expressing his knowledge and problem solving methods [87, 92, 106, 107, 108, 109, 110].

#### 4.2.3.3 System architecture

The key feature of an expert system is its strictly functional detachment of expert knowledge (knowledge base) and reasoning strategies (inference engine). This makes the system flexible and transparent. Both characteristics are crucial as expert systems are iteratively changed, updated and improved. As human knowledge permanently expands, the knowledge base of an expert system has to be expanded permanently as well. Figure 4.11 illustrates the modular architecture of an expert system.

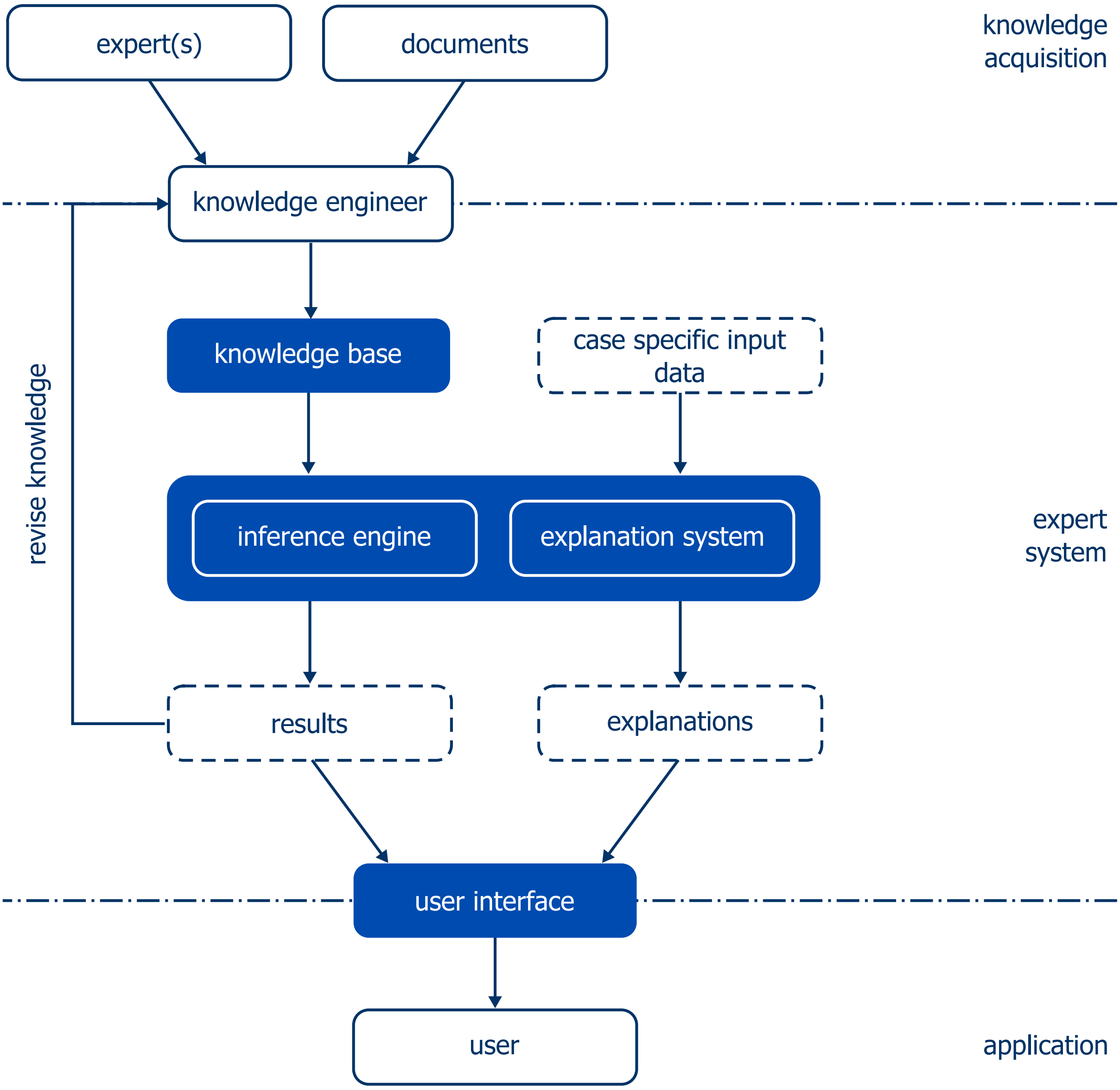



*Figure (4.11)* Architecture of an expert system [85] .

A knowledge engineer is the person who transfers knowledge from human experts, literature and other sources into the knowledge base. He is responsible for checking consistency and completeness of the knowledge.

The knowledge base comprises all the knowledge that is needed for problem solving. The knowledge can be vague, uncertain or incomplete. Knowledge can be represented in different ways, e.g. facts, rules or frames. However, a uniform representation means a simpler and more transparent system.

The inference engine provides procedural knowledge for problem solving. Procedural knowledge describes the mechanism of how case-based input data and knowledge from the knowledge base have to be applied.

Interactive systems require a dialog component (user interface) for communication with the user. The interface is used for data input, output of results and output of explanations.

The explanation component is substantial for system transparency. Explanations help the user to understand the structure and functions of the complex software system. The degree of comprehensibility on how the system acts and why it acts in a certain manner highly influences the acceptance of the system. Explanations justify why a question is asked and how results are derived. They are also an instrument to check plausibility of results [86, 87, 89, 92, 93, 106, 111, 112].

#### 4.2.3.4 Knowledge acquisition

The objective of knowledge acquisition is to ascertain, interpret and represent different kinds of knowledge (figure 4.12). Knowledge can be declarative or procedural. Declarative knowledge is a pure description of facts and heuristics, e.g. rules of thumb that were approved empirically. Procedural knowledge describes the way actions are performed. Meta knowledge is another kind of knowledge which is often described as 'knowledge about knowledge'. Meta knowledge supervises the selection and execution of knowledge and procedures. It also comprises knowledge about what oneself knows and about when and how knowledge and procedures are utilized. The steps of knowledge acquisition are executed iteratively.

Knowledge engineering comprises the steps knowledge acquisition, integration and maintenance (figure 4.12). Knowledge engineering is an iterative process. To check whether the system works as it is supposed to, the system has to solve problems that did not emerge during knowledge acquisition. Modifications are implemented subsequently.

In preparation of knowledge acquisition, the following basic questions have to be answered [91]:

1. Who has to work with the system?
2. What demands does the user make on the system?
3. What terms are used?

Knowledge acquisition is performed with the intention to model the expert's problem solving behavior. Knowledge originates from experts, literature, empirical data and other sources. A wide range of methods can be applied to extract knowledge [85, 92]:

- interview,
- questionnaire,
- presentation by expert,

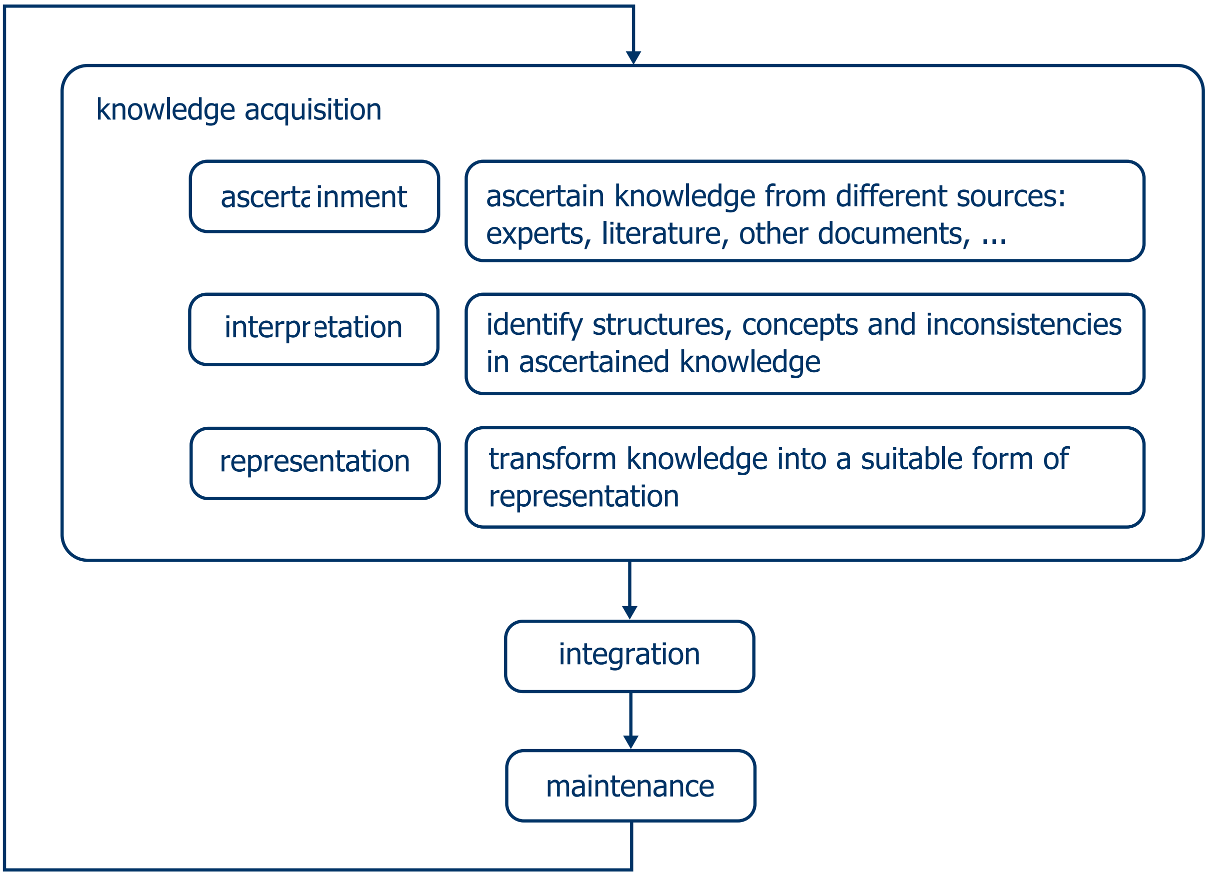



*Figure (4.12)* Process of knowledge engineering, including the step knowledge acquisition [91].

- on-site observation (observe expert while solving a problem in real environment),
- simulated environment (observe expert while working through sample problems),
- discussion/ group discussion, and
- analysis of protocols.

After being ascertained, knowledge has to be interpreted. This means to analyze and structure knowledge, to find basic relations and concepts, to find gaps and inconsistencies in the ascertained knowledge [81, 85, 91, 92, 111].

#### 4.2.3.5 Challenges of knowledge acquisition

Knowledge is ascertained from several sources. Hence redundancy is exploited. The entire collection of knowledge sources can be more robust than a single source. However, an open question is how to reconcile differing and conflicting views among experts.

The intuitive character of an expert's problem solving behavior was explained in section 4.2.3.2. An expert does not always consciously make decisions. He automatically captures the given situation and is often not aware of facts that influence his decision making. Hence, he is not always able to describe or explain what he does. This makes knowledge acquisition challenging and limits the capacity of expert systems. Extracted knowledge is often ill-specified and incomplete. The expert system is not as powerful as the expert. Knowledge ascertainment has to help the expert to explicate his knowledge. The challenge which knowledge ascertainment is faced to, is to extract hidden knowledge. The success of knowledge ascertainment is highly influenced by the following features [85, 87, 106]:

- the specificity of information,
- the similarity of condition,
- the time delay between the real problem solving situation and the occasion when the expert explains his actions and strategies.

The more specific a task, the easier it is for the expert to explain his problem solving strategies. The more similar the situation while ascertaining knowledge is to the real situation, the easier it is for the expert to pronounce his strategies. Similarity of condition also includes the time available for problem solving. If an expert can concentrate longer than usual, he tends to think more about the problem than usual. His behavior in real environment would be more intuitive. It is important to generate a context that makes it possible to reproduce problem solving behavior. The shorter the time delay after the real problem solving behavior, the easier it is for the expert to remember actions and strategies. The challenge of knowledge acquisition is to extract the knowledge which the expert actually utilizes.

### 4.2.4 Search techniques

#### 4.2.4.1 Introduction

For complex problems there is often no analytical description how to reach the goal. In this case search techniques can be used to systematically explore a space of problem states. These search techniques are also known as state space search. The problem solving procedure is represented as a path in a graph from a start state to a goal state. A graph is a set of states and a set of arcs that connect the states. State transition operators are applied to transform a state into its successor. The goal to reach can be defined explicitly by a certain goal state or implicitly by evaluation criteria, e.g. an objective function that associates a quality to the current state [74, 83, 95, 113, 114].

An example of a state-space search is given in figure 4.13. A trader has three jugs with different volumes, one with 9 liters, one with 7 liters and one with 4 liters. The 9-liter jug is filled with wine, the others are empty. Thus, the start state is $[9, 0, 0]$. The goal is to have six liters of wine in the 9-liter jug and three liters of wine in the 4-liter jug.

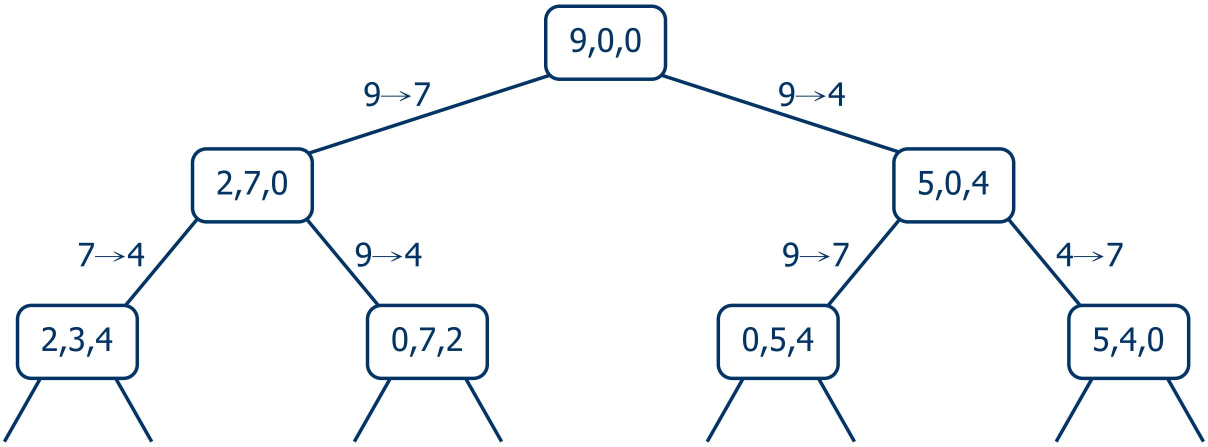



*Figure (4.13)* A part of the state-space graph for the wine jug problem [95].

Thus, the goal state is $[6, 0, 3]$. State transitions are achieved by filling wine from one jug into another. This is expressed in the form $7 \rightarrow 4$. In this example, the wine from the 7-liter jug is filled into the 4-liter jug.

#### 4.2.4.2 General features

There are various forms of search techniques. The most important classification criteria are listed below (table 4.6). Uninformed and heuristic search techniques are explained in more detail in the following sections. In section 4.2.6 genetic algorithms are introduced as an example for a nature inspired population-based search technique that applies both deterministic and stochastic operators.

In state space search two contradictory criteria must be considered. On the one hand, the search space has to be explored to guarantee a diversification of solutions. On the other hand, the space in the vicinity of promising solutions has to be exploited, which means an intensification of search.

To avoid loops, an OPEN and a CLOSED list are maintained. The OPEN list contains the untried states that have not yet been visited. The CLOSED list contains all expanded states, the states that have already been visited. This common feature of search techniques avoids that fruitless paths are repeated. Figure 4.14 shows an example with closed states. At state $[2, 3, 4]$ the operators $9 \rightarrow 7$ and $7 \rightarrow 9$ would lead to states that have already been visited. Hence, the moves from $[2, 3, 4]$ to $[0, 5, 4]$ and $[5, 0, 4]$ are not allowed. The state $[2, 3, 4]$ has only one legal successor, state $[6, 3, 0]$.

*Table (4.6)* Classification criteria for search techniques [74].

| | |
|---|---|
| uninformed<br>∘ no use of additional information about the problem domain | heuristic<br>∘ use of additional information about the properties of the specific problem domain |
| nature inspired | non nature inspired |
| deterministic<br>∘ using the same initial solution will lead to the same final solution | stochastic<br>∘ random rules are applied<br>∘ the same initial solution may lead to different final solutions |
| population-based<br>∘ a whole population of solutions is evolved<br>∘ a solution is also called an individual<br>∘ exploration oriented | single solution based<br>∘ a single solution is manipulated and transformed during search<br>∘ exploitation oriented |
| iterative<br>∘ start with a complete solution and transform it at each iteration | greedy<br>∘ start from an empty solution<br>∘ at each step a decision variable of the problem is assigned until a complete solution is obtained |

#### 4.2.4.3 Uninformed search

The uninformed search is a blind search. No domain specific knowledge is used to judge where the solution is likely to lie. The main categories of uninformed search are:

- breadth-first search,
- uniform cost search, and
- depth-first search.

In breadth-first search the search space is explored level by level. Only when no more states to be explored are left at a given level, then the search is continued at the next deeper level. In other words, the states are expanded in order of their proximity to the

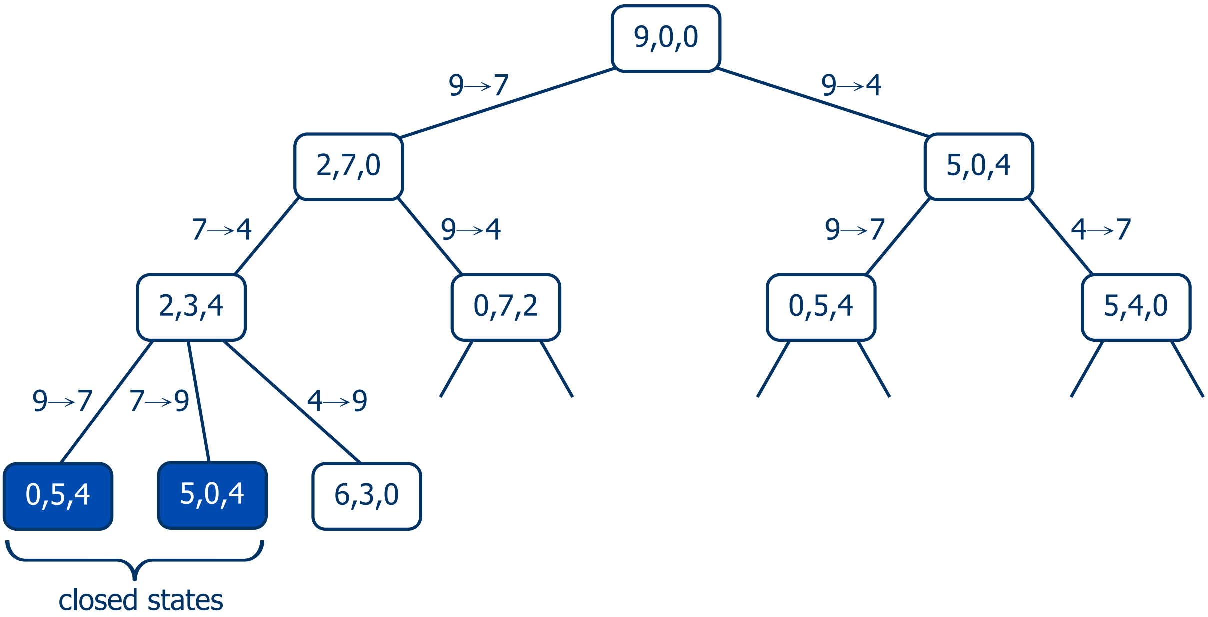



*Figure (4.14)* Closed states in state-space search.

start node. The distance between states is measured by the number of arcs between them. The search terminates when a goal state has been found. If a solution to the desired goal exists, the breath-first search algorithm is guaranteed to find the shortest possible solution sequence. The disadvantage of the breadth-first search, due to its exploration oriented characteristic, is its large computation time.

The uniform cost search tries to find the cheapest path from the start state to a goal state. A non negative cost is associated with each transition from one state to a successor state. The uniform cost search reduces to breadth-first search if all transitions have equal cost.

Depth-first search is an exploitation oriented algorithm. In depth-first search, the children of a state and their descendants are expanded before the siblings of the state are examined. In other words, the search goes deeper into the search space whenever it is possible. Alternate paths are only considered when the search reaches a dead end. A dead end is a state that has no successors. In contrast to breadth-first search, when a solution path is found, it is not necessarily the shortest solution path. It is possible to apply a depth bound to avoid that the search goes too deeply into a fruitless path [83, 95, 113].

#### 4.2.4.4 Heuristic search

The above described search techniques are exhaustive search techniques. The algorithm searches through the entire search space. For some problems the computational cost of finding a solution using these exhaustive search techniques may be too high. Heuristic search techniques attack this issue by guiding the search along paths that have high probability of success. Heuristic search techniques use additional information about the properties of the specific problem domain to search the given space more efficiently and to find a solution within a practical length of time. In contrast to the above described uninformed search techniques, heuristic search is an informed technique.

Heuristics are often rules of thumb that are based on experience or intuition. A heuristic can be considered as an informed guess on the next step to be taken in solving a problem. As a heuristic is a guess and not exact knowledge, it can lead to suboptimal solutions or fail to find any solution at all.

Best-first search is a sub domain of heuristic search. The OPEN list is implemented as a priority queue. The states in the OPEN list are ordered according to a heuristic estimate of their closeness to the goal. At each iteration, the first state of the OPEN list is expanded. The heuristics used to estimate the potential of a state range from subjective estimates to measures based on the probability of the state leading to the goal [74, 83, 95, 113, 114].

### 4.2.5 Objective function

The objective function of a search problem formulates the goal to achieve. It associates with each solution $s$ in the search space a real value that describes the quality of a solution to solve the given problem:

$$f:\ S \rightarrow \mathbb{R} \tag{4.29}$$

where $f$ is the objective function and S the set of solutions $s$. The objective function is also called cost, utility, evaluation or fitness function. Population-based search techniques need only the relative or competitive fitness to select a solution. In a relative fitness assignment a rank is associated with each individual in the population. Relative fitness assignments are used when it is impossible to associate an absolute value with all solutions. In the case when an absolute value can be associated with each solution but an analytical formulation of the objective function does not exist, the objective function is called a black box objective function (figure 4.15).

The function $f:\ S \rightarrow \mathbb{R}$ is called a black box function if [74]:

- the domain $S$ of solutions is known,
- it is possible to measure or simulate $f$ for each solution $s$, and
- no other information for the function $f$ is available.


*Figure (4.15)* Objective function as a black box [74].

An important class of optimization problems are interactive optimization problems where the result has to fit particular user preferences. An analytical formulation of the objective function does not exist. The quality of a solution is derived by a subjective evaluation of the solution by a human.

### 4.2.6 Example - genetic algorithms

Genetic or evolutionary algorithms are abstract computer models based on natural genetics and the evolution process. The concept of the survival of the fittest is used to iteratively find individuals with higher fitness. Genetic algorithms (GAs) are explained here because they incorporate many features that are characteristic for search algorithms (see also table 4.6)

With GAs solutions of the problem to be solved are represented as individuals. There are various possibilities of the formal description of individuals. Strings composed of binary values (0,1) are very common. The set of individuals is called the population. As there exist several individuals, hence several potential solutions, search is not only performed at one place in the search space but at several places simultaneously.

The suitability of an individual to the problem is indicated with a fitness value. The fitness function (also called objective function) encodes desired characteristics of the solution. The fitness is a measure to compare individuals with each other.

Although there are many variations of genetic algorithms, the basic elements are common for all variations (figure 4.16). A genetic algorithm starts with generating an initial population. This can either be done randomly, or using existing knowledge about attributes of an optimal solution. Then the fitness of the individuals of the initial population is calculated. In the next step, individuals are selected for reproduction. Generally, individuals with higher fitness are selected with higher probability. However, the exact method and the number of individuals that are selected depend on the given problem. Standard selection methods are for example:

- ranking (the best N individuals are selected),
- roulette wheel (stochastic selection),
- tournament (individuals are randomly taken from the population and the individual with the highest fitness is the one which is selected for reproduction).

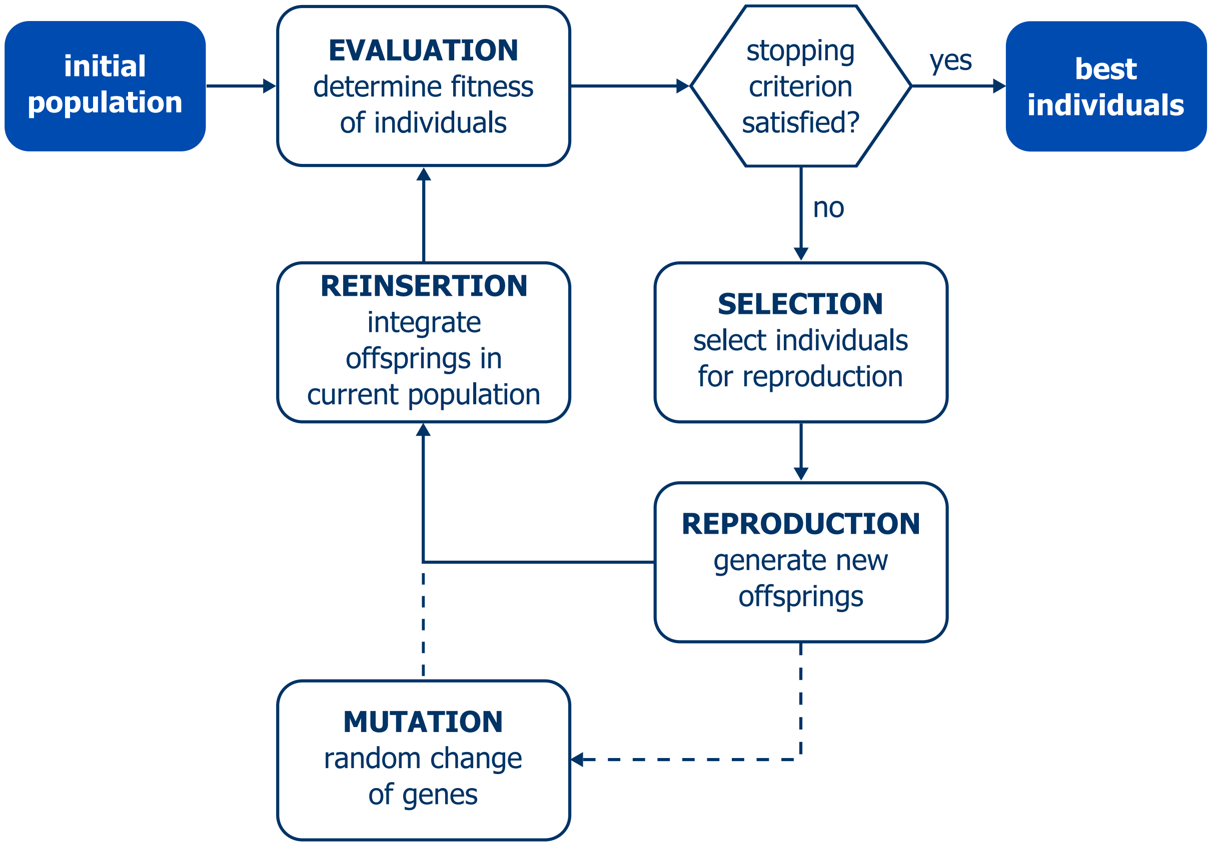



*Figure (4.16)* The architecture of genetic algorithms according to [115].

Reproduction is performed using crossover. Attributes of the parents (selected individuals) are inherited to generate offsprings. Both the number of crossover points and the number of parents can vary, e.g unary crossover (one crossover point) using two parents. The offsprings, the new potential solutions, contain only attributes that already exist in the current population. To bring new attributes into the population, mutation on selected individuals is applied. Mutation is a random modification with the purpose to produce diversification. When a population gets stuck in a local optimum, mutation is the only way to leave it. The frequency of mutation is normally small. It is not performed in each iteration. After offsprings have been generated, they are integrated in the current population. There are different possible replacement strategies. It has to be defined how many and which individuals are replaced, and how many and which offsprings are inserted. After the fitness values for the new population has been calculated, a stopping criterion is checked. Common stopping criteria are:

- a maximum number of generations,
- a condition for a good solution,
- a maximum computation time.

Normally, several stopping criteria are combined to guarantee that the genetic algorithms terminates.

Genetic algorithms are not suitable when the calculation of the fitness of the individuals is expensive [74, 84, 95, 100, 114, 115, 116].

### 4.2.7 Conclusions

AI methods are applied in problem domains that rather require qualitative reasoning and where efficient exact algorithms to solve the problem are not available. AI aims to automate intelligent behavior, such as reasoning and learning. The two most fundamental fields of AI are knowledge representation and algorithms needed to apply that knowledge. These algorithms are in general called search techniques. Knowledge representation includes both the procedure of knowledge acquisition and the decision on the most suitable form of how to represent the knowledge.

Expert knowledge on combine process optimization is available, and is suitable for use in a control system. Appropriate algorithms (analytical methods/ search methods) have to be developed that apply the expert knowledge to find a solution to the optimization problem.

As there exists no analytical formulation of the objective function (expert knowledge is of abstract form), the fitness of a solution to the problem 'optimizing combine processes' can only be determined by direct measurement. This means that each solution (=combination of settings) has to be implemented on the combine and then be evaluated. Combine processes are rather slow in dynamic. After setting changes, transient times of 20-30 sec are possible. This leads to the requirement of minimizing the number of objective function evaluations, or in other words, minimizing the number of iterations of the search. The available expert knowledge can be used in a heuristic search algorithm. Uninformed search techniques are inefficient with respect to the number of iterations and are therefore not relevant. Due to reasons of transparency, methods that apply random rules, like GAs, are also not suitable for the given optimization problem.

The, in this work, applied knowledge acquisition procedure, the resulting knowledge base, and the developed algorithms are presented in the following chapter.

# 5 Knowledge base and algorithms for optimizing combine processes

## 5.1 Specification of goals

The optimization of combine processes is a multi-dimensional and a multi-objective optimization problem. The objectives of the optimization are the harvest quality parameters (see section 2.2.2). The decision variables, the parameters that can be modified, are the combine settings (see figure 2.8). A requirement on the control system is that it works both as an interactive assistance system and an automatic control system. This requirement induces the restriction that the only parameters that can be used for control are those that are automatically adjustable while harvesting. Hence, the decision variables of the control system are the following combine settings:

- forward speed,
- rotor/ cylinder speed,
- threshing clearance,
- chaffer opening,
- sieve opening and
- fan speed.

Figure 5.1 shows the most important harvest quality parameters that have already been explained in section 2.2.2. Chopping quality and residue distribution cannot be influenced significantly by the above listed combine settings. Therefore, they are not considered in the following as objectives of optimization.

Throughput is a crucial parameter for the overall combine performance. However, operators have their preferred forward speed; the speed at which they feel comfortable. Therefore, throughput is not considered as an objective for optimization. Forward speed adjustments will not be done automatically. Adjustments of forward speed will be presented as recommendations to the operator, even in the automatic operating mode. It is up to the operator to accept or decline these recommendations. Using

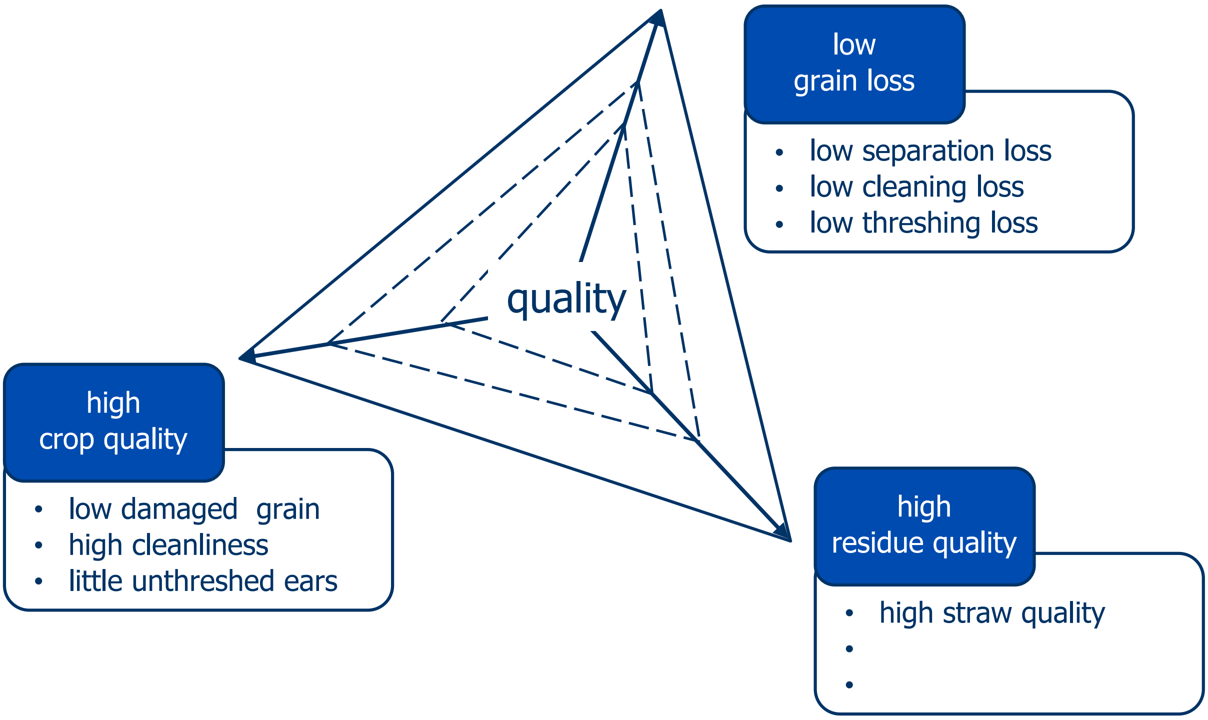



*Figure (5.1)* Objectives of optimization.

forward speed as a decision variable, but not considering throughput as an objective, incorporates the risk of reducing the overall combine performance. A decrease in forward speed will lead to a decrease in throughput (assuming same conditions). Thus, forward speed adjustments will play a special role in the following.

In the automatic operating mode, the control system uses measured signals of the quality parameters. Qualitative sensors for separation and cleaning losses and for return flow volume are already available on current production combines. Current sensor developments focus on sensors that provide absolute values. Sensors for grain quality and return flow composition are also being developed. Sensors for threshing loss and straw quality are not the focus of current sensor developments. However, the operator can evaluate these quality parameters qualitatively. He can evaluate if threshing losses are too high or satisfactory, and he can evaluate if straw quality is satisfactory of not. Thus, threshing loss and straw quality are also objectives of optimization. In the automatic operating mode, these two quality parameters will be ignored.

The return flow is added to the list of objectives. The return flow is not a direct harvest quality parameter. However, when quality and performance are not satisfactory, the return flow volume and composition provide important information about the possible problem source.

There exists no comprehensive analytical model that describes the dependencies between the selected objectives (the harvest quality parameters) and the relevant decision variables (the combine settings that can be adjusted automatically). Hence, there is no analytical objective function for the optimization of the combine processes. The most suitable model for the development of a control system is the comprehensive qualitative model from figure 3.3. It contains all the relevant qualitative correlations between combine settings and harvest quality parameters. When an expert optimizes the harvest quality, he applies a sequence of setting adjustments, starting with the setting that seems to be most promising. The existing model (figure 3.3) does not contain such sequences.

Based on the described requirements and restrictions, the following two major steps are necessary for the development of a control system for optimizing combine processes:

1. Acquisition of existing expert knowledge on combine process optimization as an enhancement to the existing qualitative model.
2. Development of a control algorithm that uses the acquired expert knowledge and that is suitable for both an interactive and an automatic operating mode.

Another requirement is that the control system can be applied both for tangential and axial combines. For reasons of simplification, the descriptions in this thesis are done on the example 'walker combine with tangential threshing drum.'

## 5.2 Knowledge base

### 5.2.1 Procedure and objectives of knowledge acquisition

The objective of knowledge acquisition is to derive a sequence of adjustments to solve issues with the quality parameters shown in figure 5.1. The issue can be that only one quality parameter is not acceptable (single-objective optimization) or that several quality parameters are not satisfactory (multi-objective optimization). For eight quality parameters the number of combinations of unacceptable quality parameters is 255. Thus, for knowledge acquisition the problem dimension was reduced to a single-objective optimization problem. The experts were instructed to concentrate on one single process parameter and define the sequence of adjustments they would apply to improve the chosen process parameter (single-objective optimization). The experts were allowed to use additional information for decision making. For example, statements like the following were given by the experts: 'If cleaning losses are too high and fan speed is low, then first increase fan speed, second ...'

Knowledge acquisition was performed with the methods 'interview', 'questionnaire', 'simulated environment' and 'on-site observation' (see section 4.2.3.4) in an iterative procedure. The first iteration of knowledge acquisition was done in spring. The disadvantage of a large time delay between the real problem solving situation (grain harvest in Germany takes place in summer and fall) and the occasion when the expert explains his actions and strategies (here spring) had to be accepted. A major requirement on the knowledge base is to find a uniform knowledge representation that is most appropriate for the given optimization problem. In this context, the term 'uniform knowledge representation' is equivalent to an operator independent, compressed and non redundant representation.

The first iteration of knowledge acquisition was carried out using the method 'simulated environment'. The experts were given sample problems which they had to solve, e.g.:

*Grain cleanliness is poor and grain moisture is low. How would you solve this problem?*

The results of the first iteration were used to get an initial overview of the scope and complexity of the problem domain. The second iteration of knowledge acquisition was done using the methods 'interview' and 'questionnaire'. The results of the second iteration were analyzed for inconsistencies and incompleteness in knowledge. The third iteration of knowledge acquisition comprised several group discussions with the experts involved in the interviews. The goal was to remove inconsistencies and to add missing knowledge.

On-site observation of an expert operator was done during the summer harvest season 2009 in Germany. The objectives were:

- the experimental verification of the already acquired knowledge in a real problem solving situation,
- identification of inconsistencies in the knowledge,
- monitoring of the problem solving procedure,
- derivation of restrictions for the control system, and
- acquisition of additional knowledge, especially meta knowledge.

The knowledge engineer monitored the expert's actions from the co-driver's seat of a walker combine during three harvest days. Environmental conditions and operator's actions were documented in a protocol. The on-site observation was done in combination with discussions with the expert operator to understand the reasons for the adjustments he implemented.

Adjustments that are made to optimize combine processes depend on the crop being harvested. Crop types were categorized into groups with similar threshing and separation characteristics. This resulted in three crop groups:

Group 1: canola, grass seeds, sunflower, ...

Group 2: wheat, barley, rye, ...

Group 3: corn, soybeans, peas, ...

Separate adjustment matrices for each combination of combine type and crop group were determined. The descriptions in the following are based on the knowledge base of a walker combine and crop group 2.

### 5.2.2 Knowledge base and meta knowledge

| issue | grain tank/ return flow composition | | | | sequence of adjustments | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | dam. grain | light MOG | heavy MOG | unthr. heads | fwd. sp. | cyl. sp. | thr. clrn. | cha. op. | sie. op. | fan sp. |
| return flow | • | | | | − D | | | + C | + A | − B |
| | | • | | | | | | − B | | + A |
| | | | • | | − C | − A | + B | | | |
| | | | | • | + C | + A | − B | | | |
| separation loss | | | | | − C | + A | − B | | | |
| | | | • | | − C | − B | − A | | | |
| cleaning loss | | | | | − E | − C | + D | + A | | − B |
| | | • | | | − E | − C | + D | + B | | + A |
| threshing loss | | | | | + C | + A | − B | + D | | |
| grain damage | | | | | + C | − A | + B | | | |
| MOG (grain tank) | | | | | | − C | + D | − A | − B | |
| | | • | | | | − D | + E | − C | − B | + A |
| unthr. heads (grain tank) | | | | | + C | + A | − B | | | |
| straw quality | | | | | + C | − A | + B | | | |

*Figure (5.2)* Adjustment matrix for a walker combine in crop group 2. The '+' and '-' signs specify the direction of the adjustment, the Latin letters specify the sequence.

Figure 5.2 shows the adjustment matrix for a walker combine in crop group 2. The adjustment matrix is one part of the knowledge base. The other part is the meta knowledge. The adjustment matrix contains the sequence of adjustments an expert operator would apply to solve a certain issue. The Latin letters define the order in which adjustments are performed. The letter 'A' specifies the setting with the highest priority, letter 'B' is equivalent to the second highest priority, and so on. The '+' and '-' signs define the direction of adjustment. The '+' represents an increase of the corresponding setting, the '-' a decrease. The bold bullets in columns 2-5 of the adjustment matrix represent the existence of additional information. Rows without a bullet are default rows. As an example, to solve the issue 'separation losses are too high' with the additional information that the relative amount of heavy MOG in the grain tank is higher than the other undesired components, an expert operator would first decrease threshing clearance, then decrease cylinder speed, and finally decrease forward speed.

During the first phase of knowledge acquisition, the experts were allowed to use several kinds of additional information that they considered appropriate for decision making. The set of additional information they used is listed in table 5.1.

*Table (5.1)* List of additional information that was used by expert operators for decision making.

| | parameter | values |
|---|---|---|
| (1) | return flow volume | normal, high |
| (2) | main component of return flow composition | damaged grain, light MOG, heavy MOG, unthreshed heads |
| (3) | main undesired component of grain tank composition | damaged grain, light MOG, heavy MOG, unthreshed heads |
| (4) | current cylinder/ fan speed operating point compared to optimal operating point | high, low |
| (5) | chaff load | normal, high |

Not all parameters in table 5.1 can be evaluated by inexperienced operators. The first three items are not critical because sensors for return flow volume are available, and sensors for return flow and grain tank composition are being developed. The grain tank composition can also be evaluated qualitatively by a look into the grain tank. Some combines offer the possibility to have a look at the return flow composition. The latter two items in table 5.1 are critical. The evaluation of the cylinder and fan speed operating points is difficult because the optimal operating ranges vary dependent on crop types and other harvest conditions. The same speed can be high for crop type A but low for crop type B. The current cylinder and fan speed values can be read from the CAN bus and the cab display. However, the estimation of the optimal ranges requires additional expert knowledge. Hence, the evaluation of the cylinder and fan speed operating points can not be delivered by sensors or by inexperienced operators. The chaff load in a combine can currently not be measured by a sensor and is difficult to be estimated even by an experienced operator.

A detailed analysis by use of meta knowledge revealed that the adjustment matrix can be restructured in a way that the complete knowledge is kept and all required information can be delivered by a sensor or the operator. Additional information about the return flow volume is already incorporated in the adjustments to solve issues with the quality parameter 'return flow'. There was an overlap in the adjustments to reduce return flow volume and in the adjustments to solve other issues while the condition (additional information) 'return flow volume = high' was true.

The cylinder and fan speed operating points correlate with the grain tank composition (see the qualitative model in figure 3.3). Increasing fan speed increases the amount of broken grain. A large amount of light MOG particles in the grain tank correlates with a low fan speed. A high amount of heavy MOG particles in the grain tank can originate from a high cylinder speed. Unthreshed heads in the grain tank correlate with a low cylinder speed. The parameters cylinder and fan speed operating point were replaced by the parameter grain tank composition.

Rows of the adjustment matrix which used additional information about chaff load could be deleted. The knowledge incorporated in these lines was already incorporated in the adjustments to reduce return flow volume. According to expert operators, there is a correlation between a high chaff load and a high return flow volume.

Finally, only two items of the additional information table (5.1) are left:

- (2) main component of return flow composition (damaged grain, light MOG, heavy MOG, unthreshed heads) and
- (3) main undesired component of grain tank composition (damaged grain, light MOG, heavy MOG, unthreshed heads).

There is also a correlation between the return flow composition and the grain tank composition. A high amount of damaged grain in the return flow correlates with a high amount of damaged grain in the grain tank, and so on. Hence, return flow and grain tank composition can be used equivalently. However, for the issue 'return flow' information about the 'return flow composition' should be used and for issue 'MOG in grain tank' the grain tank composition should be used.

Grain tank composition used as additional information overlaps with the process parameters for grain quality (grain damage, MOG in grain tank, unthreshed heads) which are defined as issues for optimization. However, this does not contradict to statement that the adjustment matrix comprises single-objective optimization problems. The grain tank composition is an evaluation of the distribution of the grain tank components. 'High amount of light MOG particles in the grain tank' means that the amount of light MOG particles is high compared to the other components (damaged grain, heavy MOG particles, unthreshed heads). It is just a comparison of the relative amounts of the four undesired components. It does not mean that there is an issue with light MOG particles in the grain tank.

In addition to the adjustment matrix in figure 5.2, important knowledge (the so-called meta knowledge) could be acquired. A summary is given below:

1. In most situations, losses have highest priority before grain damage, grain cleanliness and straw quality.
2. A high return flow volume indicates that the combine processes are not working optimally.
3. An expert always evaluates the overall combine quality. Due to the significant number of cross correlations between process parameters and settings, process parameters have to be optimized in context with each other. Process parameters are partly conflicting. Optimizing the overall combine quality requires a compromise between process parameters.
4. Only one setting is adjusted at a time. Otherwise, the identity and magnitude of an adjustment that contributed to a change in quality cannot be clearly determined.
5. The first adjustment step of a setting is relatively large. The step size depends on the current operating point. An expert applies a large step at the beginning to get an estimate of the impact of the current setting adjustment.

### 5.2.3 Discussion and conclusions

When comparing the developed adjustment matrix (figure 5.2) with the comprehensive qualitative model (figure 3.3), several differences can be found. The qualitative model shows a small influence of the chaffer opening, the sieve opening and the fan speed on separation loss. However, these three settings are not included in the adjustment matrix in the lines that correspond to the issue of high separation losses. In the adjustment matrix there are two lines referring to the issue of separation losses. The differences between the adjustments in these two lines are the sequence of cylinder speed and threshing clearance, and the direction of the cylinder speed adjustment. The latter represents the characteristic with a minimum that can also be found in the qualitative model. When threshing is too aggressive, a lot of heavy MOG is produced which impedes separation and hence increases separation losses. This state is indicated by a high amount of heavy MOG in the grain tank and/ or return flow. The second line for the issue of separation loss in the adjustment matrix corresponds to this state. Reducing cylinder speed reduces the generation of heavy MOG particles and hence reduces separation losses. The other possible cause for high separation losses is that threshing is not aggressive enough. In this case, the increase of cylinder speed reduces separation losses. This equals the first line for the issue of separation loss in the adjustment matrix. The qualitative model shows a characteristic with an optimum also for the correlation between separation loss and threshing clearance. However, the two lines for separation loss in the adjustment matrix both show a negative sign. There are also a number of other differences between the qualitative model and the adjustment matrix.

The differences between the knowledge incorporated in the adjustment matrix (figure 5.2) and the knowledge in the qualitative model (figure 3.3) can be explained with different experiences of the experts and different points of view. The sequences of adjustments to improve a single process parameter are compromises between several experts. The impact of a setting on a process parameter depends on the combine and crop type. The main differences between the combines and crops are taken into account by separate adjustment matrices for different combine and crop types. However, there exist differences in the behavior of combines of the same combine type, due to wear of the mechanical and hydraulic systems. There also exist differences in the threshing characteristic of the same crop in different regions. These specific conditions could not be captured in the adjustment matrix as this would have increased the dimension of the matrix drastically. When providing the knowledge, the experts always refer to their specific knowledge. There is probably no expert that is familiar with all existing combine and crop types. The qualitative model (see section 3.3) presents a scientific point of view. Experiences were both gathered during field tests and by laboratory analysis. The adjustment matrix represents an operator oriented point of view.

The large number of differences between the knowledge incorporated in the qualitative model (figure 3.3) and that incorporated in the adjustment matrix (figure 5.2) points out the highly uncertain character of the knowledge for optimizing combine processes. The sequence of settings in the adjustment matrix represents procedural knowledge. The adjustment matrix does not contain facts like absolute values for optimal operating points. The sequence of adjustments does not state the magnitude of correlation between a setting and a process parameter. The effect of an adjustment on a process parameter depends on the quantitative slope of the respective two-dimensional characteristic (process parameter as a function of setting value) and on the current operating point. The quantitative characteristic depends on the combine and crop type, the combine state, the crop and harvest conditions. In a flat region of the characteristic even a large adjustment might result in an insignificant change of the process parameter.

The sequence of settings in the adjustment matrix is a compromise between several experts. There is no guarantee that the recommended sequence is the most efficient procedure in all possible situations. The sequence of settings has to be interpreted in the following way: The setting with priority A has the highest confidence to improve the respective process parameter, the setting with priority B has the second highest confidence, and so on. The sequence represents a relation between confidences. The adjustment matrix does not contain numeric values for confidences or probabilities. Thus, standard representations for uncertain knowledge, like certainty factors, Bayesian probabilities or belief intervals according to Dempster-Shafer (see section 4.2.2.2), are not suitable. Furthermore, the knowledge in the adjustment matrix can not be represented by fuzzy logic. Fuzzy logic would be suitable if knowledge on combine process optimization contained rules like the following: "If separation losses are *high*, then increase cylinder speed by a *large* amount." However, the existing knowledge base does not contain knowledge of that form. There is no information about the amount of a process parameter or the size of a setting.

The highest uncertainty in the knowledge base is incorporated in the direction of the adjustments. Additional information in form of the grain tank and return flow composition is used to reduce uncertainty with respect to the direction of the adjustment. However, considerable uncertainty is still left. The adjustment matrix does not cover the variety of conditions that exist during harvest, either because the conditions were not expressed by the experts, or because the complexity of the adjustment matrix would be too high otherwise. The involved experts were not able to rate their confidence in the directions they have chosen. Neither the certainty factor formalism, nor Bayesian probability or the Dempster-Shafer belief intervals can be used as a representation of the incorporated uncertainty. A measure of uncertainty is not available.

Based on the above described characteristics of the available knowledge on combine process optimization, several requirements on the control algorithm can be derived:

1. Due to the uncertainty in the direction of the adjustments, the control algorithm has to detect if the wrong direction has been chosen.
2. If a false direction of an adjustment has been applied, the control algorithm has to react by a change in direction.
3. All relevant settings have to be taken into account, no matter their priority, as the magnitude of the influence of a setting on the process parameters is unknown.
4. The control algorithm has to try all relevant settings until the optimal performance is reached or no further improvement can be achieved.
5. A suitable algorithm has to be identified that is capable of determining the size

of an adjustment. The only available knowledge that can be used by the algorithm, is the current operating point, the physical ranges of a setting and the meta knowledge described in the previous section.

6. The algorithm must memorize previous adjustments in order to prevent these previous adjustments from being reversed and getting the algorithm stuck in an infinite loop.
7. The algorithm must stop when all quality parameters are satisfactory.

## 5.3 Control algorithm for setting adjustment determination

In the previous section the expert knowledge on combine process optimization and the utilized knowledge acquisition procedure were described. The current section describes the key features of the control algorithm that uses the acquired expert knowledge to solve single and multiple issues with quality parameters.

### 5.3.1 Architecture of control system

The architecture of the control system is shown in figure 5.3. The *Steady State Detection* block is responsible for detecting if the combine processes are in a steady state. Quality can only be evaluated if the combine processes are in a steady state. The block *Quality Evaluation* detects issues with quality parameters based on sensor data. This block is only used in automatic mode. In the interactive mode the operator provides qualitative feedback on the quality parameters. The *Setting Adjustment Determination* block selects the setting to be optimized and determines the step sizes. The *Supervisory Logic* triggers the *Steady State Detection* block, the *Quality Evaluation* block and the *Setting Adjustment Determination* block. The *Signal Surveillance* block detects invalid input signals and determines when the control has to go into a suspended state.

The *Setting Adjustment Determination* is the core part of this thesis and will be described in more detail in this section.

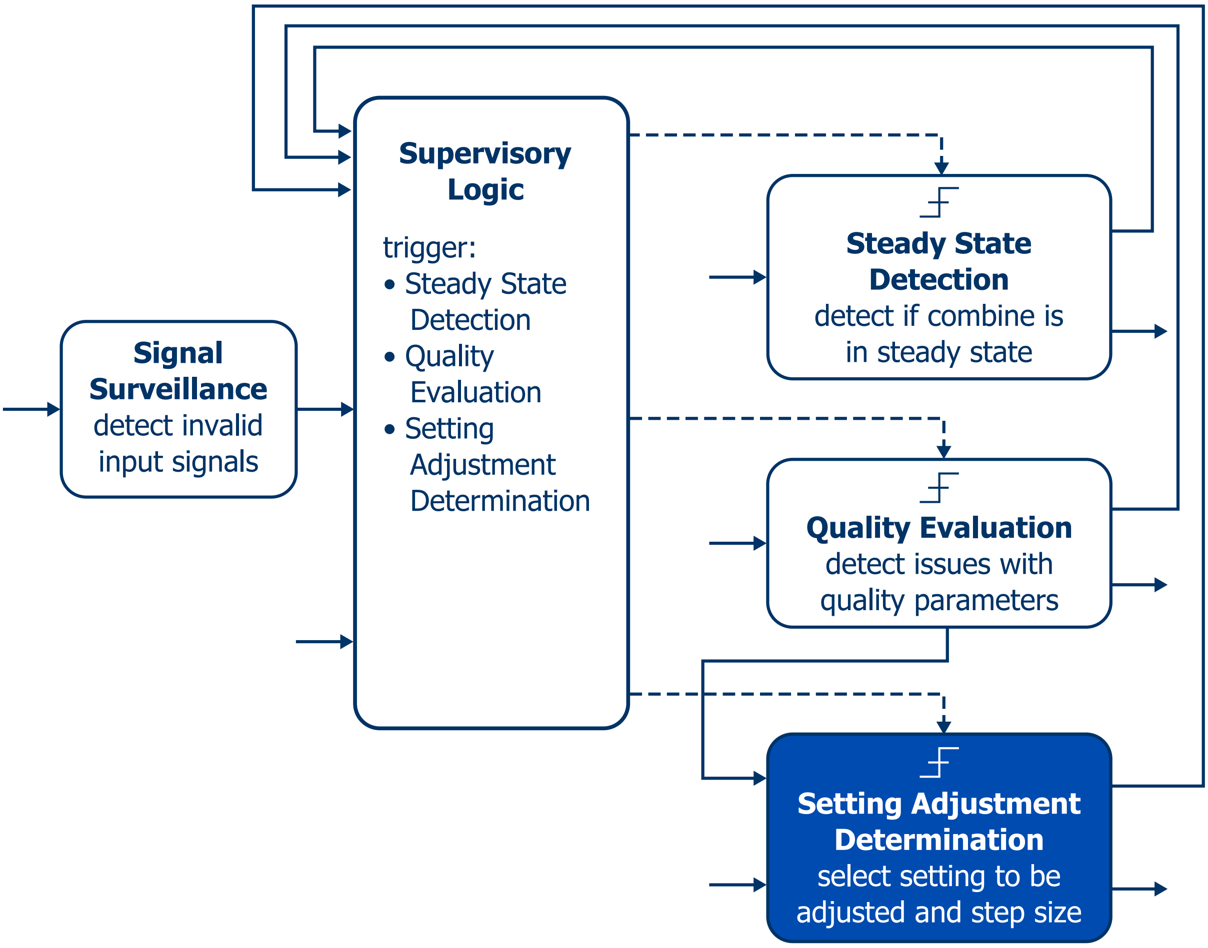



*Figure (5.3)* Architecture of the developed control system with the core part *Setting Adjustment Determination*.

### 5.3.2 Top level work flow of setting adjustment determination

The adjustment matrix (figure 5.2) and the explanations in section 2.2.2 have shown that the objectives of optimization are highly conflicting. It is not possible to optimize all quality parameters at the same time. Improving one specific quality parameter means that others get worse. The solution to this optimization problem is thus a set of Pareto optimal operating points. These are operating points that lead to a good compromise between the quality parameters. There exists no unique global optimum. Different operator preferences lead to a different solution in the Pareto optimal set.

The goal of the control algorithm for setting adjustment determination is to bring unsatisfactory quality parameters to a satisfactory level and to maintain this quality level. For the first part of this goal (bringing unsatisfactory quality parameters to a satisfactory level) the interactive operating mode will be applied, using qualitative operator evaluation of quality parameters. The second part of the goal (maintaining the desired quality level) will be handled by the automatic operating mode.

The given optimization problem - optimizing combine processes - is a multi-dimensional and multi-objective optimization problem. The independent decision variables are the combine settings forward speed, cylinder speed, threshing clearance, chaffer opening, sieve opening and fan speed. The objectives of the optimization problem are the combine quality parameters of separation loss, cleaning loss, threshing loss, broken grain, cleanliness, unthreshed material in the grain tank, straw quality and return flow. Hence, the dimension of the optimization problem is 8 x 6; 8 quality parameters and 6 settings. For performance optimization it is necessary to maximize the throughput. However, knowledge acquisition (see section 5.2) has revealed that the operators set their preferred forward speed where they feel comfortable. Therefore, throughput is not considered as an objective for optimization. The goal is to optimize some combination of the quality parameters.

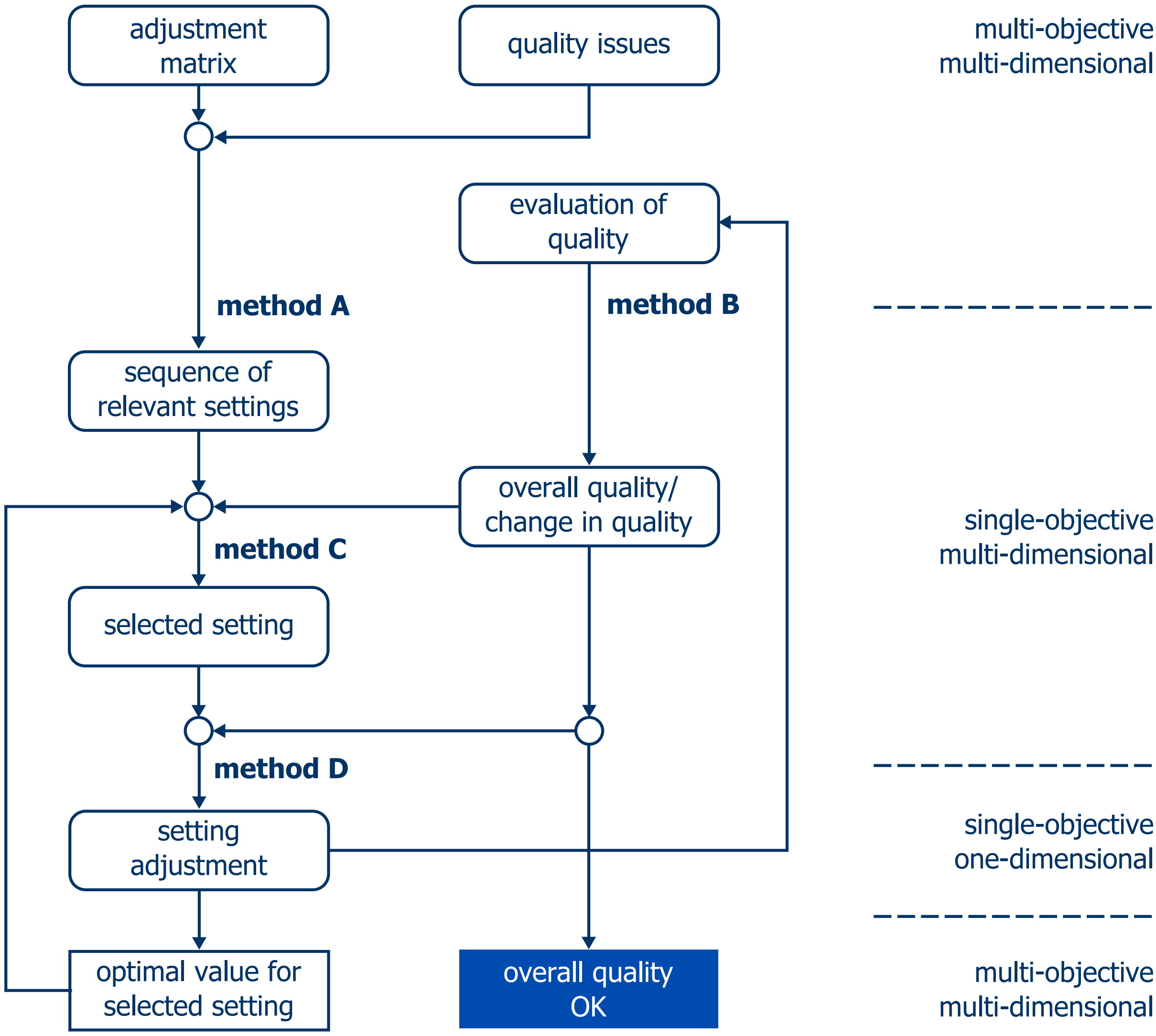



*Figure (5.4)* Top level work flow of *Setting Adjustment Determination* algorithm.

Figure 5.4 shows the top level work flow of the *Setting Adjustment Determination* algorithm. The following meta knowledge items (see also section 5.2.2) were used to define the top level work flow:

- An expert always evaluates the overall combine quality. Due to the significant number of cross correlations between process parameters and settings, process parameters have to be optimized in context with each other. Process parameters are partly conflicting. Optimizing the overall combine quality requires a compromise among process parameters.
- Only one setting is adjusted at the time. Otherwise, the identity and magnitude of an adjustment that contributed to a change in quality cannot be clearly determined.
- Operator satisfaction is both the activation trigger and the stop criterion for the optimization. The control algorithm starts when at least one quality parameter is not satisfactory. The algorithm terminates when all quality parameters are satisfactory.

As explained in chapter 4.1.4, a multi-objective optimization problem can only be solved by transformation into a single-objective optimization problem. At first, a suitable transformation for the given problem has to be found. The resulting single-objective optimization problem is multi-dimensional. There exist direct search algorithms and gradient-based search algorithms for multi-dimensional optimization. Gradient-based algorithms require (as the name says) the gradient of the objective function. As there exists no analytical formulation of the objective function, gradient-based algorithms cannot be applied. The second type of multi-dimensional optimization algorithms, direct search algorithms, do not require gradients or an analytical formulation of the objective function. However, they are based on the comparison of several function values in each iteration. For the given optimization problem, $n+1=7$ function values have to be compared. In the interactive operating mode, the operator would have to do this evaluation. This would mean that the operator has to modify the combine settings 7 times, memorize the 8 quality parameters for each of the 7 combinations of combine settings and then make a comparison. This is simply impossible. Only in the automatic operation mode, a direct search algorithm for multi-dimensional optimization would be. As a consequence, the complexity of the optimization problem must be further reduced. Figure 5.4 shows the top level work flow of the developed solution for the given optimization problem

The basic principle to solve the given multi-objective optimization problem is a transformation into one-dimensional single-objective optimization problems which are solved iteratively (see figure 5.4). Several methods have been developed that are applied sequentially. At first, a sequence of settings is generated that are relevant for solving the given quality issues. The corresponding method (method A) performs a state space search to transform the multi-objective optimization problem into a single-objective optimization problem. Based on the adjustment matrix and (several) existing quality issues, a sequence of setting adjustments is generated which is most suitable for solving these issues. Method A uses mainly mathematical calculations. In contrast to method A which considers only the quality parameters that are not satisfactory, method B determines the overall combine quality and the overall change in quality based on single evaluations of all eight quality parameters. Method B is a rule-based method which also transforms a multi-objective optimization problem into a single-objective optimization problem. The results of method A (sequence of relevant settings) and method B (overall combine quality/ overall change in quality) are then utilized by method C. With the use of information about the overall combine quality and additional meta knowledge, method C selects one setting from the sequence of relevant settings which have potential to solve the given issues. In the interactive mode, operator decisions also play a role in the selection of the setting. The actions of method C are equivalent to a transformation of the multi-dimensional optimization problem (several relevant settings for adjustment) into a one-dimensional optimization problem (one setting is selected). In order to find the optimal value for the selected setting, method D then performs one iteration of a one-dimensional optimization, using the Golden Section search algorithm. After each iteration of method D, the calculated setting value is implemented on the combine. The change in quality is then evaluated, either by the operator or by sensors. As soon as a new evaluation is available, method B comes into action again. Methods B, C and D are applied iteratively until a solution is found or all relevant settings have been exhausted.

The four methods A-D are the core part of the control system and will be explained in detail in this section.

### 5.3.3 Method A - Generate sequence of relevant settings

For generating a sequence of relevant settings based on the adjustment matrix and current quality issues, a heuristic search method has been chosen. Apart from the adjustment matrix and the quality issues, additional information is used in the form of operator preferences and in special cases, which gives the search method its heuristic character. Another important character of the search algorithm is its deterministic character. The same combination of adjustment matrix and quality issues always results in the same sequence of settings. This is important for reasons of transparency. The operator is able to understand how the control system works because its actions are traceable. Random rules are not suitable for the given optimization problem. Therefore, genetic search algorithms (as described in section 4.2.6) were not applied. In addition, standard transformations from a multi-objective to a single-objective optimization problem (as described in section 4.1.4) cannot be applied because there are no analytical descriptions of the objective functions. With the given optimization problem, the objective functions are the quality parameters as a function of the combine settings. As a result, a heuristic state space search is used to generate the sequence of relevant settings.

In the easiest case, there is only one issue. The sequence of relevant settings is then equal to the sequence of adjustments in the knowledge base (figure 5.2) for the given (single) issue. When there is more than one issue, the relevant settings might have different impacts on the quality parameters that are not satisfactory. For example, in order to improve threshing loss, the first adjustment is an increase in cylinder speed (see figure 5.2). However, cylinder speed must be decreased (as the third relevant setting) if cleaning losses are too high. In this case, there is a conflict. A compromise must be found both for the order of the settings and the directions of the setting adjustments. The ideal case is that the adjustments of the same setting all have the same sign. Settings which fulfill this condition are taken first by the optimization algorithm. When there are different signs for the adjustments of the same setting (considering the relevant quality parameters), then there is a conflict. The question is: Which direction of adjustment should be applied? The quality parameters are prioritized. It is more important so solve issues with the quality parameters that are of highest priority. The direction of adjustment is chosen in a way that the adjustment improves the quality parameters with the highest priority. In general, settings which do not produce a conflict are taken first. The higher the conflicting character of a setting, the lower is its relevance for solving the given issues. The degree of conflict of a setting is described by a numeric cost value. Figure 5.5 shows the work flow of the algorithm that determines this numeric cost value.

In order to explain how the numeric cost value is calculated and how the sequence of settings is derived from the cost value the following example is used:

- The combine is a walker combine and the crop is wheat. Hence, the adjustment matrix from figure 5.2 is used.
- There are currently issues with cleaning losses and MOG in the grain tank. The grain tank composition shows that the light MOG particles are dominating.
- The operator preferences are:
  1. Losses
  2. Grain damage
  3. Grain cleanliness
  4. Straw quality

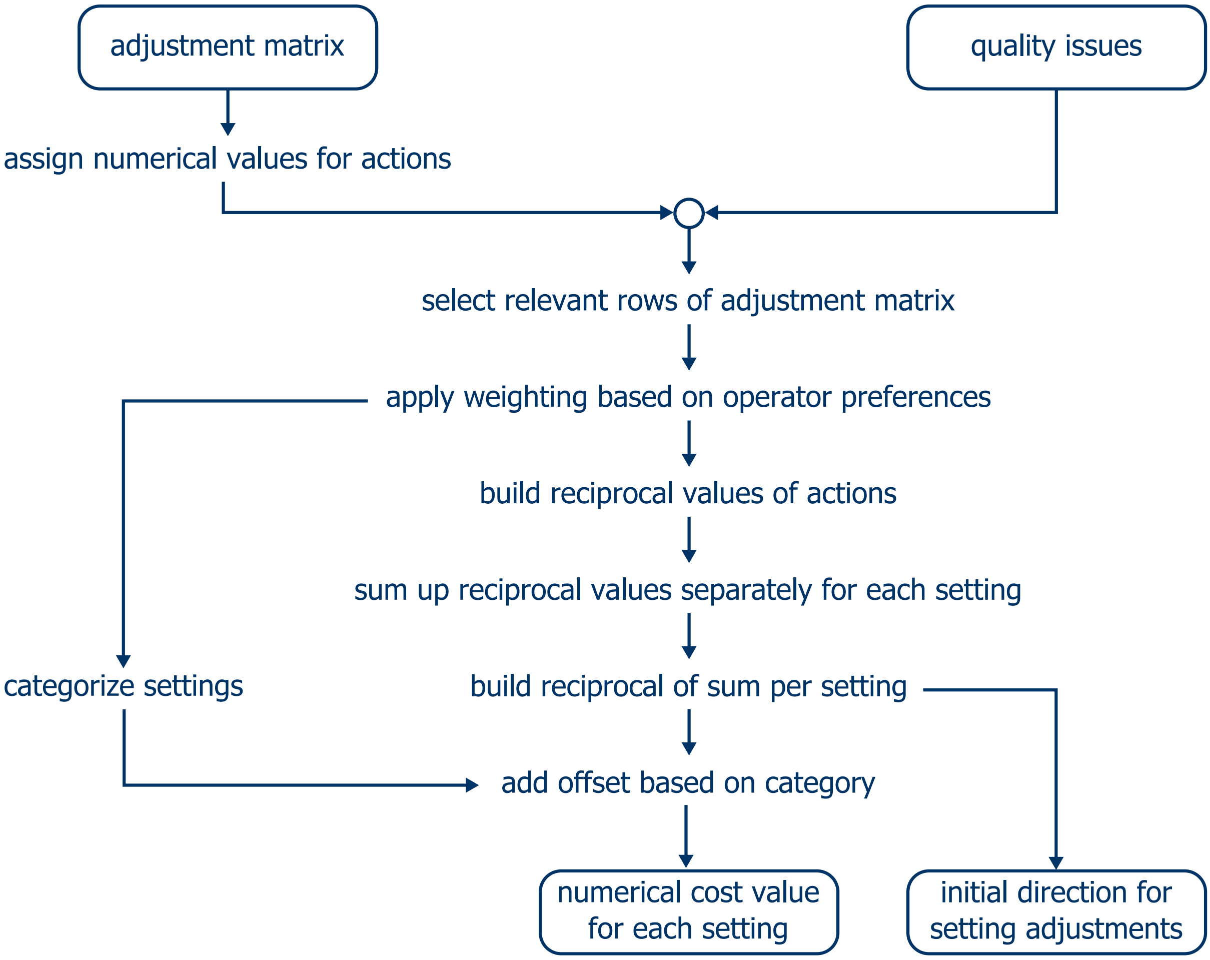



*Figure (5.5)* Assignment of numeric cost values that characterize the degree of conflict of each relevant setting.

The cost values and directions of adjustment of the above example are shown in table 5.2.

*Table (5.2)* Example - Cost value and direction of adjustment per setting.

| setting | forward speed | cylinder speed | thresh. clrn. | chaffer opening | sieve opening | fan speed |
|---|---|---|---|---|---|---|
| direction of adjustment | - | - | + | + | - | + |
| cost value | 115 | 6.5 | 8.6 | 209 | 112 | 2 |

The cost values for each setting (values are taken from table 5.2) are now used as the costs for the state transitions in the state space graph (figure 5.6). The goal of the state space search is to find the path with the lowest cost. The optimization of combine settings is terminated when all quality issues are resolved or no relevant setting is left.

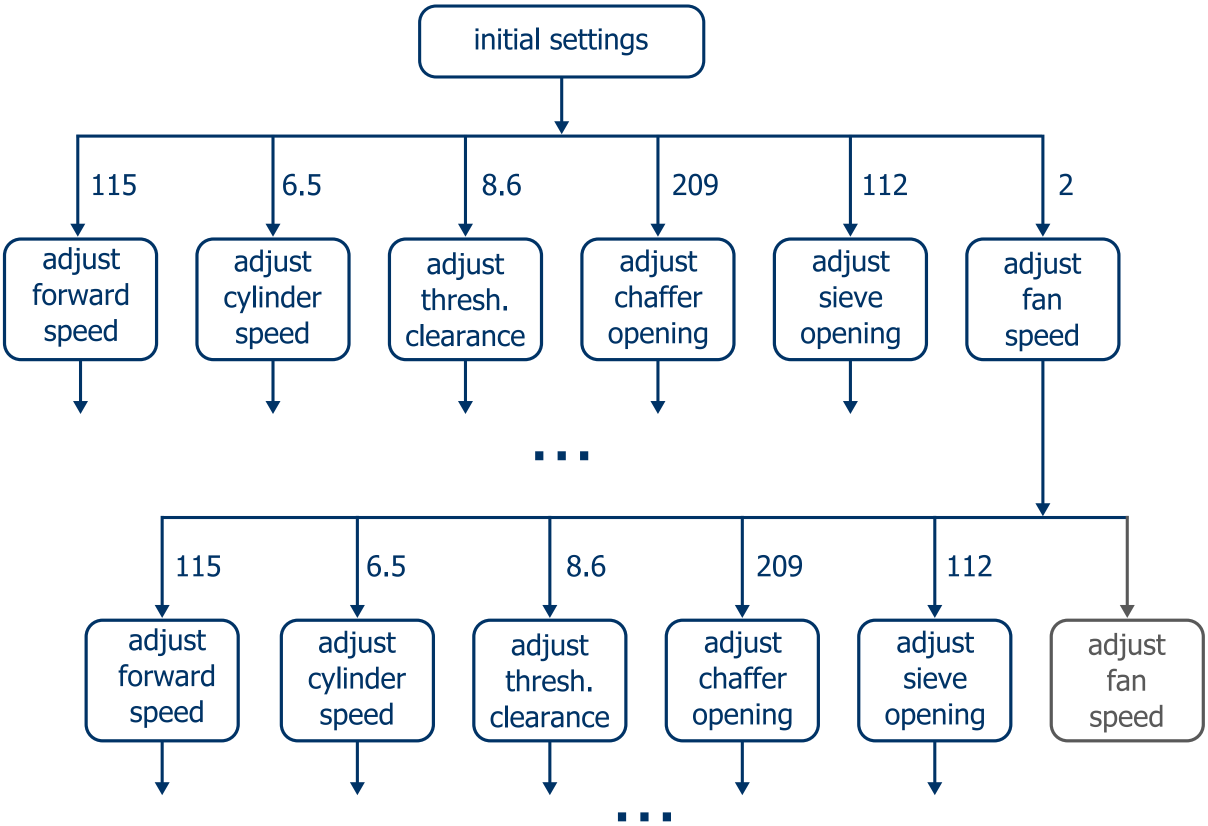



*Figure (5.6)* State space graph to determine the optimal sequence of settings for the given example.

It is obvious that the path with the lowest cost is the one that applies setting changes in the order of ascending cost values.

In this example, fan speed is the first setting to be adjusted because the cost value 2 is the minimum of all costs. Cylinder speed has the second lowest cost value. The resulting sequence of adjustments and their initial direction for the given example are:

1. fan speed (+)
2. cylinder speed (-)
3. threshing clearance (+)
4. sieve opening (-)
5. chaffer opening (+)
6. forward speed (-)

The adjustment of the chaffer opening is applied before the adjustment of forward speed although forward speed has the lower cost. This is a special case: A decrease of forward speed is always the last adjustment. In addition to that, forward speed adjustments can be declined by the operator because they might reduce throughput, and hence, might reduce the overall combine performance.

### 5.3.4 Method B - Determine overall quality and overall change in quality

Method B determines the overall combine quality and the overall change in quality based on single evaluations of the eight quality parameters. For each of the quality parameters an evaluation is available that gives information if there is an issue with the quality parameter and if the quality has changed. In the interactive operating mode, the evaluations are provided by the operator. In the automatic mode, the *Issue Detection* block provides the quality evaluation based on sensor information. As there are no sensors for threshing loss and straw quality, these two quality parameters are, in the automatic operating mode, considered as being permanently satisfactory.

Method B is a rule-based method that performs a transformation of a multi-objective optimization problem (eight quality parameters) into a single-objective optimization problem (overall quality/ overall change in quality). The multi-objective optimization problem is characterized by the detached evaluations of the eight quality parameters. Several logic operations have been defined in order to derive overall combine quality and overall change in quality. The logic operations also provide information about conflicts between quality parameters. Another output of method B is the information if the situation regarding the quality issues has changed and therefore the sequence of relevant settings has to be updated. This is for example the case when there is a cleaning loss and a MOG issue (see example in previous subsection) and the MOG issue has been resolved after fan speed, cylinder speed and threshing clearance have been optimized. When there is no longer a MOG issue, the sieve opening is no longer a relevant setting for adjustment because the sieve opening does not have an impact on the remaining cleaning loss issue.

### 5.3.5 Method C - Select setting from list of relevant settings

Method A generates a sequence of settings that are relevant for solving quality issues. The selection of one setting from this sequence is handled by method C. Method C uses meta knowledge, the overall quality and operator interactions to decide which setting to select (figure 5.7). In a special case when the initial setting value is very close to the physical limit and the direction of adjustment points beyond this limit, the stop condition for the optimization of the selected setting is true in the first iteration. In this case the selected setting is moved to the end of the sequence of settings and will later be used with the opposite direction of change. This transition condition takes into account that the knowledge in the adjustment matrix is uncertain and the initial direction of adjustment might be wrong. The second condition check comprises the

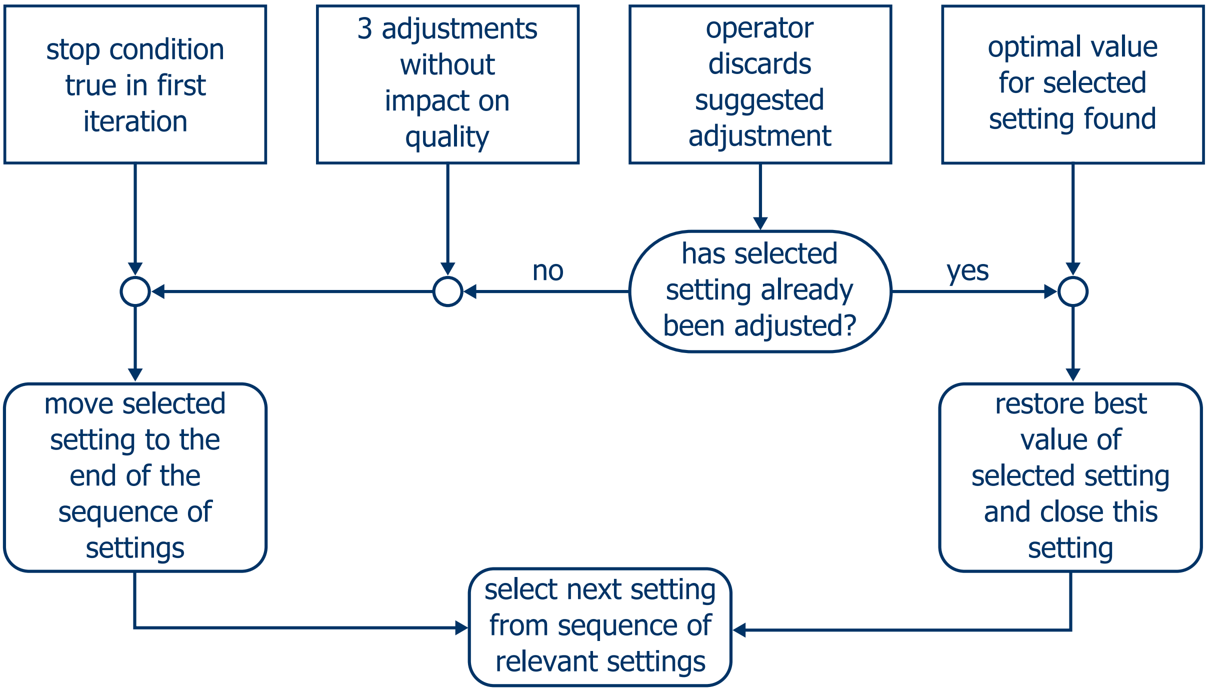



*Figure (5.7)* Method C - conditions for transition to the next setting in the sequence of relevant settings.

number of times the setting has been adjusted and the number of times there had been no impact on quality. If the setting has been adjusted three times without any impact on quality, the currently selected setting is moved to the end of the sequence of relevant settings and will be adjusted again after the remaining settings have been optimized. This condition comprises the meta knowledge that in some conditions the impact of a setting is only seen after a very large adjustment. If the operator discards a proposed adjustment (only possible in interactive mode), it is checked if the setting has been adjusted before or if this was the first adjustment proposition for the currently selected setting. If the setting has not been adjusted before, the setting is moved to the end of the sequence of relevant settings. If the setting has already been adjusted, then the best known value for this setting is restored and the setting is closed. This means that this setting will not be changed any more. The last condition that results in a transition to the next setting in the sequence of settings is that the optimal value for the currently selected setting has been found. Method C is applied after each evaluation of the quality. Method C represents a transformation of the multi-dimensional optimization problem (several relevant settings for adjustment) into a one-dimensional optimization problem (one setting is selected).

### 5.3.6 Method D - Find optimal value of selected setting

By applying methods A, B and C, the multi-objective and multi-dimensional optimization problem could be transformed into a single-objective and one-dimensional optimization problem that is solved iteratively. Optimization methods for this type of optimization problems have been described in section 4.1.2. The major restriction for the selection of the optimization method is that the objective function is not available in analytical form. The objective function is a black box function (see section 4.2.5, figure 4.15). The solution (the combination of settings) and the quality is known but not the analytical relation between the two. Therefore, only the Golden Section search is applicable. The Golden Section algorithm determines the next step by comparing function values. Hence, an analytical description of the objective function and derivatives are not necessary. Only the qualitative relation between the current quality and the best occurred quality has to be known. This relation is derived from the variable $fbetter$, the best setting value and the newly calculated setting value (see table 5.3). The value of the variable $fbetter$ is determined by method B and has the following characteristic:

- $fbetter = -1$ if the overall quality got worse,
- $fbetter = 0$ if there is no change in overall quality, and
- $fbetter = 1$ if the overall quality was improved.

*Table (5.3)* Quality relation derived from $fbetter$, the best setting value and the newly calculated setting value, with $x_1 < x_2$.

| fbetter | best value | new value | search direction | quality relation |
|---|---|---|---|---|
| $-1$ | $x_2$ | $x_1$ | negative | $f(x_1) > f(x_2)$ |
| $-1$ | $x_1$ | $x_2$ | positive | $f(x_1) < f(x_2)$ |
| $\{0, 1\}$ | $x_1$ | $x_2$ | positive | $f(x_1) > f(x_2)$ |
| $\{0, 1\}$ | $x_2$ | $x_1$ | negative | $f(x_1) < f(x_2)$ |

The value $fbetter = 0$ is treated equal to $fbetter = 1$. As a consequence, the search direction is kept if there has been no change in overall combine quality ($fbetter = 0$). This procedure is consistent with the procedure an expert would apply when there is no change in overall quality.

There are several aspects of the original Golden Section search (see section 4.1.2) that are not applicable for the optimization of combine settings:

1. The data resolution is defined by the utilized data type.
2. There is no minimal step size.
3. There is no maximal step size.

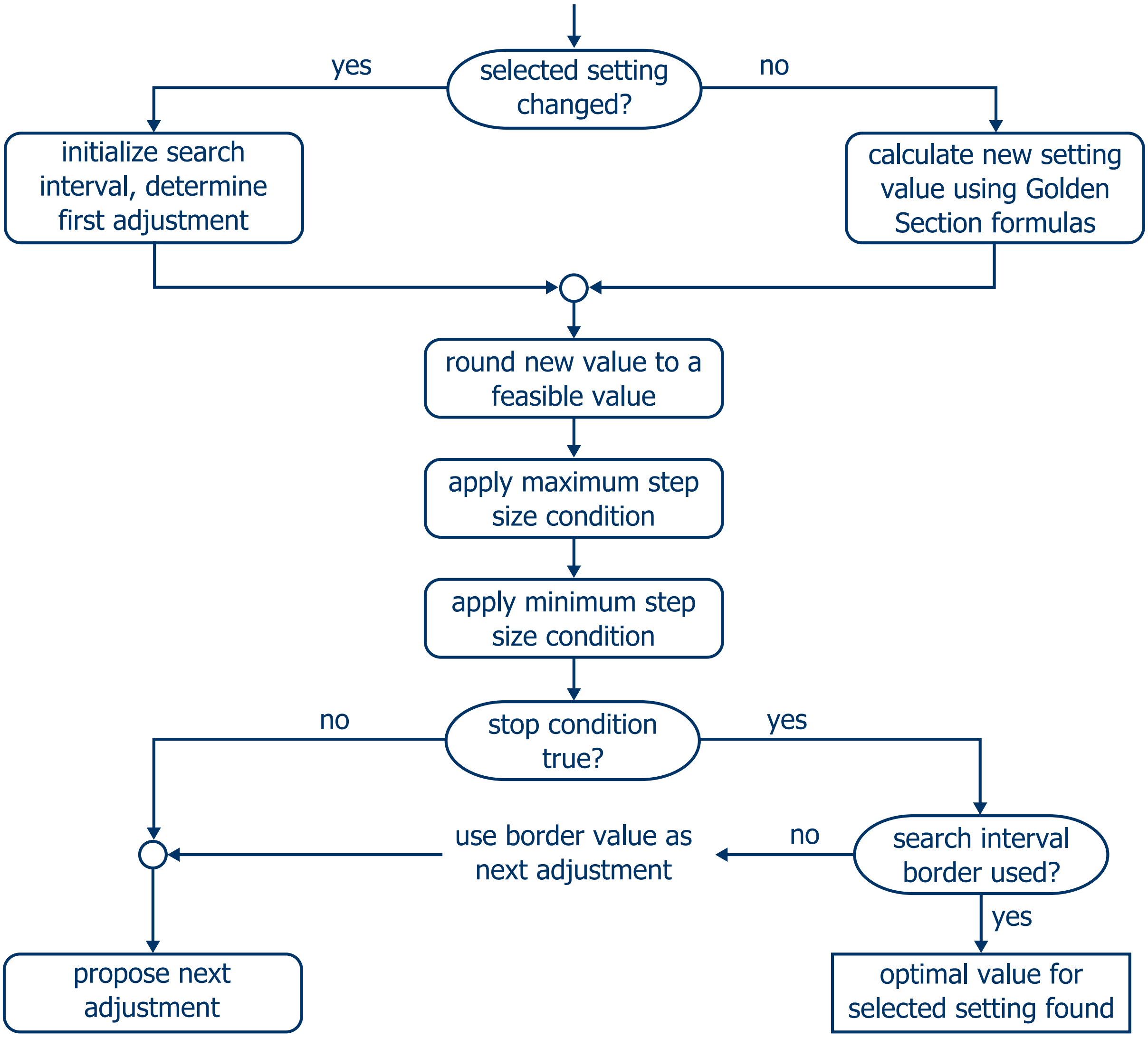



*Figure (5.8)* Method D - adaptation of Golden Section search to combine characteristics.

4. The initial borders of the search interval $[a_0, b_0]$ cannot be reached.

Hence, the following adaptations have been made due to the characteristics of the combine process (see also figure 5.8):

1. The proposed adjustment is rounded to a feasible value. Forward speed adjustments are rounded to 0.1 kph, cylinder speed and fan speed adjustments are rounded to 10 rpm, threshing clearance, chaffer and sieve opening adjustments are rounded to 1 mm.
2. Minimum step sizes are necessary because too small adjustments will not result in a visible change in quality. The respective values are 0.2 kph for forward speed and 1 mm for threshing clearance, chaffer and sieve opening. The minimum step sizes for cylinder speed and fan speed depend on the crop type and vary

between 20 rpm and 40 rpm. The minimum step size must be respected both for the difference between the best setting value and the new value, and for the difference between the previously proposed setting value and the new setting value.

3. Maximum step sizes have been introduced to avoid jumping around in the search interval and to prevent the search from going into a region with little potential for improvement. For each crop type there exists a feasible range where the optimal setting value probably is located. The maximum step sizes depend on crop type and the current best setting value. The distance between the best setting value and the new setting value must not exceed the maximum step size.
4. When the stop condition is true, each of the current borders of the search interval is checked to determine if it is still the same as the initial border of the search interval ($a_n = a_0$ or $b_n = b_0$). If yes, the stop criteria is ignored and the unused border value ($a_n$ or $b_n$) is applied as the next proposed adjustment.

The initial search interval for a setting and the first adjustment (new proposed setting value) are determined based on the direction of adjustment from the sequence of relevant settings (see method A), the physical limits for the setting and the basic Golden Section formulas. If the direction of adjustment is negative, then

$$a_0 = physical\ minimum\ of\ current\ setting \tag{5.1}$$

$$b_0 = \frac{1}{c} \cdot (current\_setting\_value - a \cdot (1 - c)) \tag{5.2}$$

$$x_1 = a_0 + (1 - c) \cdot (b_0 - a_0) \tag{5.3}$$

$$new\ value = x_1 \tag{5.4}$$

If the direction of adjustment from the sequence of settings is positive, then

$$b_0 = physical\ maximum\ of\ current\ setting \tag{5.5}$$

$$a_0 = \frac{1}{c} \cdot (current\_setting\_value - b_0 \cdot (1 - c)) \tag{5.6}$$

$$x_2 = a_0 + c \cdot (b_0 - a_0) \tag{5.7}$$

$$new\ value = x_2 \tag{5.8}$$

The stop condition is true if one of the following conditions is fulfilled:

$$b_n - a_n < 2 \cdot minimum\ step\ size(selected\ setting) \tag{5.9}$$

$$new\ value < a_n \tag{5.10}$$

$$new\ value > b_n \tag{5.11}$$

The two latter conditions are necessary because the new value can be outside of the search interval due to rounding and the minimum step size condition.

In addition to the above described adaptations, there is one more special case. This concerns the case when the search is terminated after the first adjustment because the adjustment made quality worse and one of the physical limits is reached. Instead of stopping the optimization of the currently selected setting, the direction of adjustment is reversed and the search interval is initialized again. Thus the uncertainty of the knowledge in the adjustment matrix is respected.

## 5.4 Summary

The result of the knowledge acquisition procedure is a knowledge base with six adjustment matrices for different crop and combine types. The adjustment matrices contain problem oriented setting adjustment recommendations in order to solve issues with quality parameters. The large number of differences between the knowledge incorporated in the qualitative model (figure 3.3) and that incorporated in the developed knowledge base (figure 5.2) points out the highly uncertain character of the knowledge for optimizing combine processes. The sequence of settings in the adjustment matrices is a compromise between several experts. There is no guarantee that the recommended sequence is the most efficient procedure in all possible situations. Standard representations for uncertain knowledge are not suitable because there is no information about the estimated amount of impacts. A major requirement on the control algorithm, which utilizes the acquired knowledge, is flexibility. The algorithms must recognize false search directions and must react appropriately.

The given optimization problem - optimizing combine processes - is a multi-dimensional and multi-objective optimization problem. The basic principle to solve the given multi-objective optimization problem is a transformation into one-dimensional single-objective optimization problems which are solved iteratively. Several methods have been developed that are applied sequentially.

# 6 Verification and validation of control system

## 6.1 Scope and purpose

The core part of the control algorithm is the block *Setting Adjustment Determination* (see figure 5.3). This block has several parameters that must be configured. The two most crucial are the minimum and the maximum step size of the settings. These two parameters determine to a large extent the number of iterations which are necessary to find the optimal setting values. The number of iterations are crucial for the overall performance of the control system. Minimum and maximum step size are directly used by method D (see section 5.8). In order to investigate the influence of the minimum and maximum step size and to determine the optimal values for these parameters, an isolated simulation of method D has been done. The results are presented in section 6.2.

The overall performance of the control algorithm is analyzed by closed loop simulation, using an existing scalable combine model [117]. The evaluation criteria are the percentage of improvement, the simulated machine adjustment time, and the final forward speed. Closed loop simulation is done with the entire control system as it is shown in figure 5.3. However, the goal is to asses the performance of the block *Setting Adjustment Determination*. When using ideal sensor signals and when assuming constant field conditions, the influence of the two other main blocks *Quality Evaluation* and *Steady State Detection* can be neglected. The block *Setting Adjustment Determination* uses only preprocessed data, and not direct sensor signals. A combine model provides simulated signals for all quality parameters. The signals are smooth and do neither contain random process variation nor sensor noise.

## 6.2 Isolated simulation of method D

The purpose of the isolated simulation of method D is to analyze the influence of the minimum and maximum step size on the number of iterations, and to determine optimal values for these parameters. The initial search direction also has an impact on the number of iterations. The question shall be answered if there are disadvantages when the initial search direction is wrong. A further parameter that influences the number of iterations is the start value. The start value of the optimization is given. The investigation of the influence of the start value has been done to show the possible range of scenarios between best case and worst case. The simulations in this section are done on the example cylinder speed with a physical range of $[450,\ 1000]\ rpm$.

### 6.2.1 Simulation method

The number of iterations that are necessary to find the optimal value for a setting depend on the shape and the absolute range of the two dimensional characteristics between settings and quality parameters (see figure 3.3). There exists a large spectrum of different characteristics in the field. It is not possible to consider all of them in the simulation. In order to draw general conclusions from the simulation results, an abstract simulation method has been chosen. Based on the variables $fbetter$ and $fconflict$ the recommended setting value of the next iteration is calculated (see also section 5.3). The variables $fbetter$ and $fconflict$ describe if the overall combine quality has been improved and if there has been a conflict between different quality parameters, respectively.

*Table (6.1)* Possible combinations of the input variables to method D, $fbetter$ and $fconflict$.

| $fbetter$ | $fconflict$ | combination possible | state name |
|---|---|---|---|
| $-1$ | $0$ | yes | S1 |
| $-1$ | $1$ | yes | S2 |
| $0$ | $0$ | yes | S3 |
| $0$ | $1$ | no | - |
| $1$ | $0$ | yes | S4 |
| $1$ | $1$ | no | - |

A state space search that finds all possible sequences for the combinations of the variables $fbetter$ and $fconflict$ has been implemented. The possible combinations are listed in table 6.1. Figure 6.1 shows the structure of the search tree. The depth of the paths and the total number of paths are a result of the state space search. The influencing factors are the minimum and maximum step size, the initial search direction and the start value of the setting.

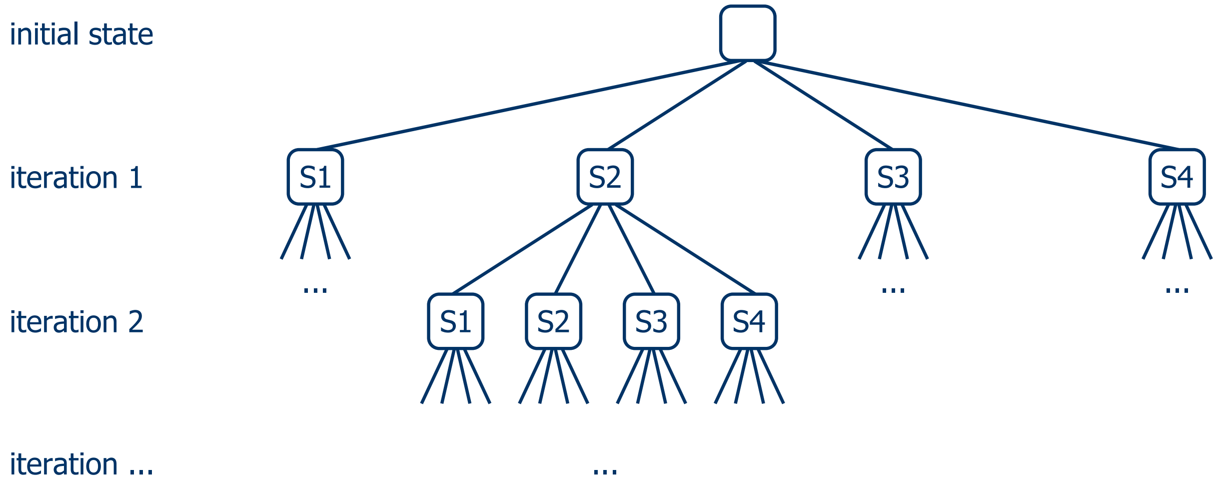



*Figure (6.1)* Search tree for generating all the possible sequences of the combinations of $fbetter$ and $fconflict$.

### 6.2.2 Influence of minimum and maximum step size

Figure 6.2 shows the minimum (ItMin), maximum (ItMax) and average number (ItMean) of iterations over the minimum step size. The larger the minimum step size, the lower the minimum, maximum and average number of iterations. However, the influence is small. The average number of iterations for a minimum step size of $20\,rpm$ is between $6.3$ and $7.4$ for different start values and initial search directions.

A stronger influence can be seen in figure 6.3. The higher the maximum step size, the lower the average number of iterations. A similar correlation can be seen for maximum step size and maximum number of iterations. The minimum number of iterations increases with increasing maximum step size. The reduction of the average number of iterations from a maximum step size of $100\,rpm$ to a maximum step size of $150\,rpm$ is insignificant. With a lower maximum step size, the algorithm jumps around less and is easier to trace by an operator. Maximum step sizes of $50\,rpm$ and less result in significantly higher average and maximum number of iterations. Therefore, a maximum step size of $100\,rpm$ should be chosen.

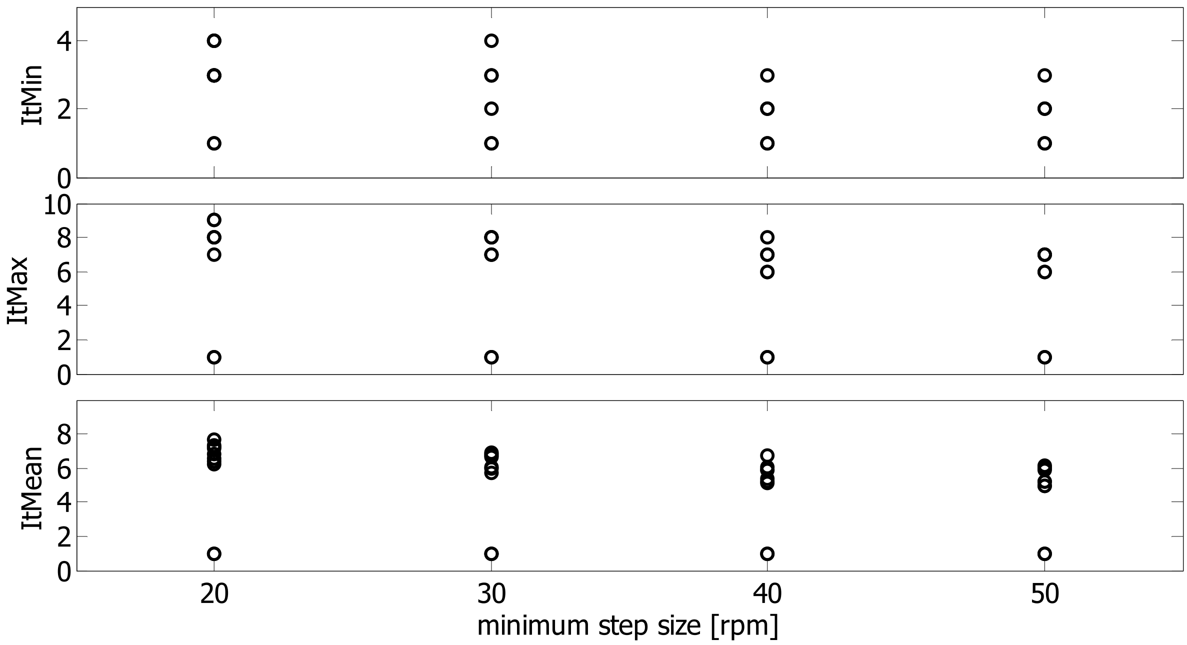



*Figure (6.2)* Minimum, maximum and average number of iterations over minimum step size with a maximum step size of $100\,rpm$.

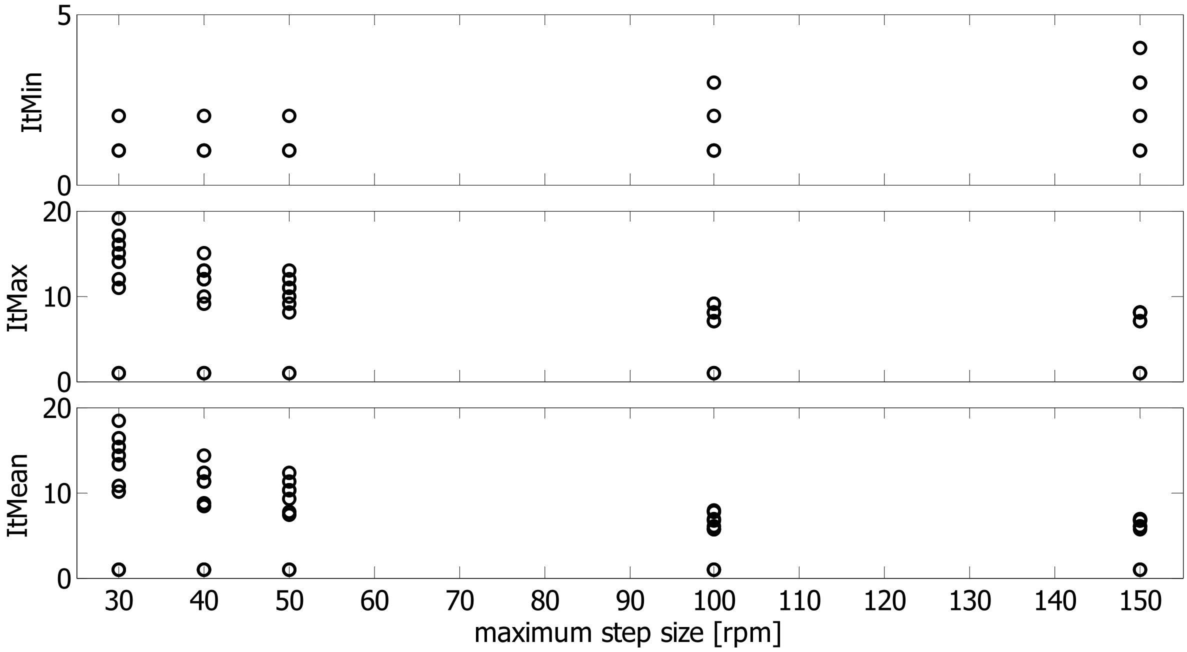



*Figure (6.3)* Minimum, maximum and average number of iterations over maximum step size with a minimum step size of $30\,rpm$.

Figures 6.4 shows the average number of iterations over the start value for a negative initial search direction, and for different minimum and maximum step sizes. In the upper plot, the best value found by the method D lies in the same direction as the initial search direction denotes. In the bottom plot, the best value lies in the opposite direction of the initial search direction. In other words: In the upper plot, the best value is smaller than the start value. In the bottom plot, the best value is higher than the start value. When the best value lies in the opposite direction of the initial search direction, the average number of iterations is slightly higher. The slope of the curves describes the influence of the start value. If the difference between minimum and maximum step size is small, the slope is high. The worst case is equal minimum and maximum step sizes. The average number of iterations and the influence of the start value is smallest when there is a clear difference between minimum and maximum step size.

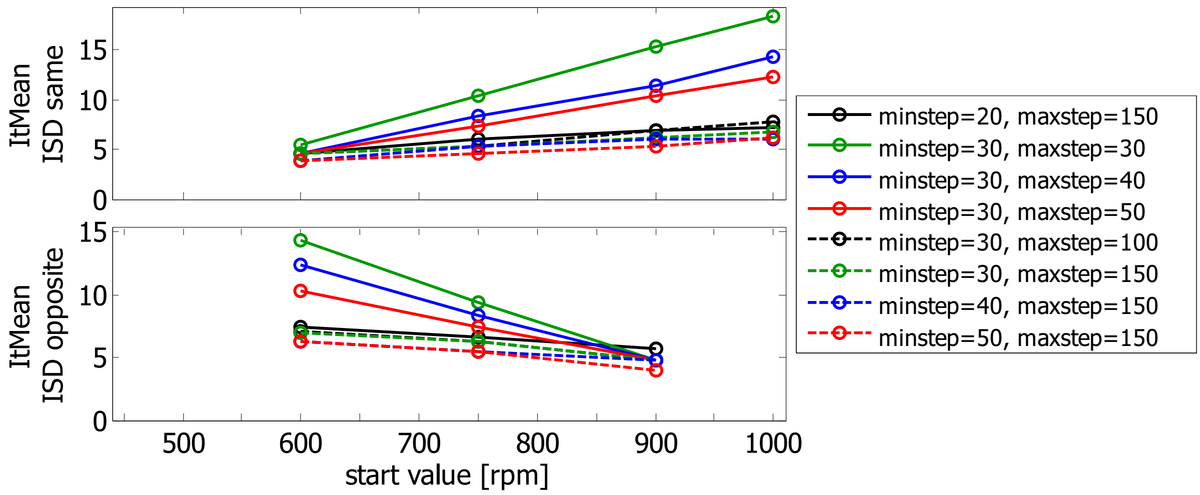



*Figure (6.4)* Average number of iterations over start value for negative initial search direction (ISD).

The above findings for the negative initial search direction are also true for a positive initial search direction (see figure 6.5).

As a result, a maximum step size of $100\ rpm$ and a minimum step size of $20 - 30\ rpm$ is recommended. The minimum step size must be large enough to show a change in quality. It must be small enough to guarantee that the derived optimum is close enough to the actual optimum. Otherwise performance is wasted.

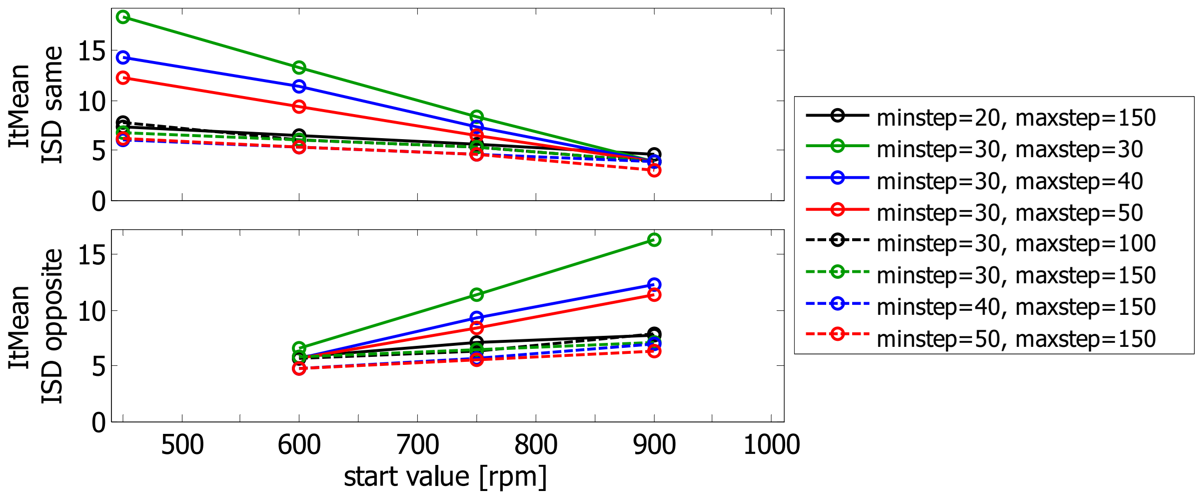



*Figure (6.5)* Average number of iterations over start value for positive initial search direction (ISD).

### 6.2.3 Influence of initial search direction

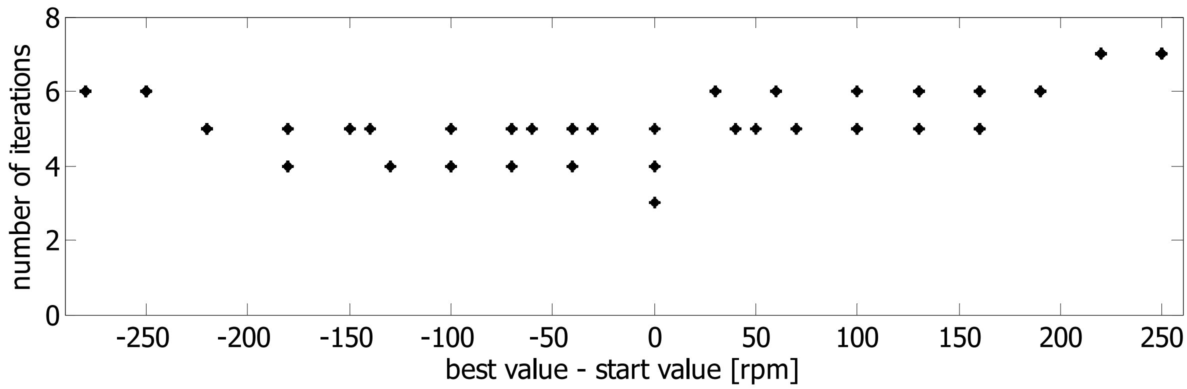



*Figure (6.6)* Number of iterations over the difference between best value and start value for a start value of $750\ rpm$ and a negative initial search direction.

Figures 6.6 and 6.7 show the influence of the initial search direction on the number of iterations. The minimum and maximum step sizes were $30\ rpm$ and $100\ rpm$, respectively. In figure 6.6 the initial search direction is negative. The number of iterations is lower when the best value is smaller than the start value. In figure 6.7 the initial search direction is positive. The number of iterations is lower when the best value is higher than the start value. This means, the number of iterations is smaller when the initial search direction points in the correct direction. In case the search starts in the wrong direction, one iteration more is necessary. However, the influence of the initial search direction is much lower than the impact of the minimum and maximum step size.

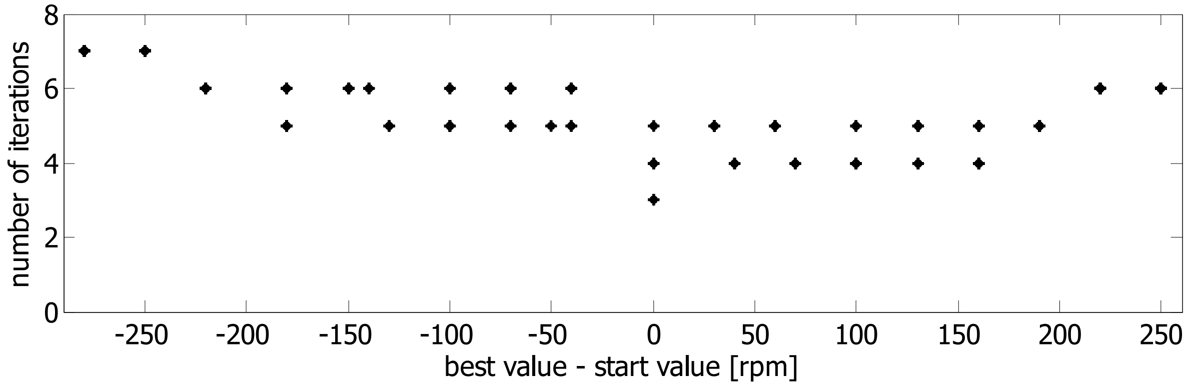



*Figure (6.7)* Number of iterations over the difference between best value and start value for a start value of $750\,rpm$ and a positive initial search direction.

### 6.2.4 Influence of start value

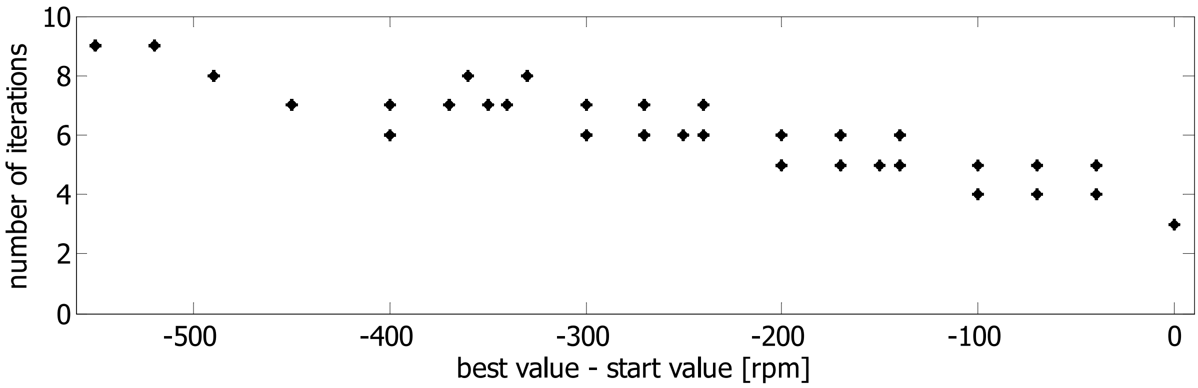



*Figure (6.8)* Number of iterations over the difference between best value and start value, with start value $1000\,rpm$, initial search direction negative, minimum step size $30\,rpm$, maximum step size $100\,rpm$.

The larger the difference between the best value and the start value, the more iterations are necessary to find the optimal setting value (figure 6.8). The number of iterations is lower when the search starts near the optimal value. However, this can not be influenced in field conditions. The start value is defined by the operator and the best value is defined by current conditions.

The larger the distance of the start value to the physical limit to which the initial search direction points, the more dominating are the higher number of iterations (figures 6.9 and 6.10). The start value $750\,rpm$, the middle of the physical range, shows the most favorable distribution of iterations.

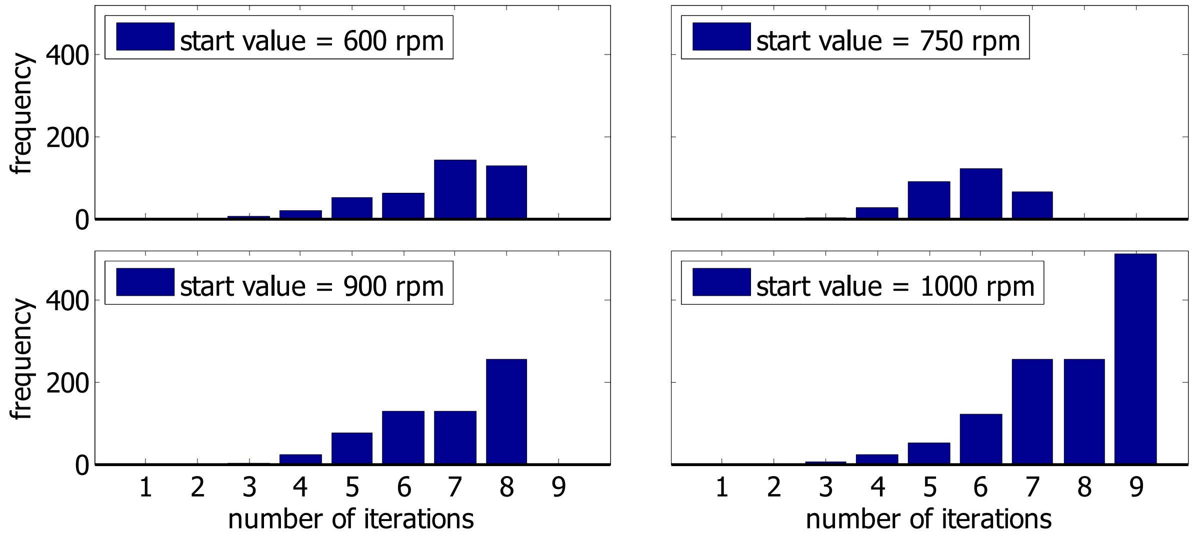



*Figure (6.9)* Frequency of number of iterations for different start values and negative initial search direction.

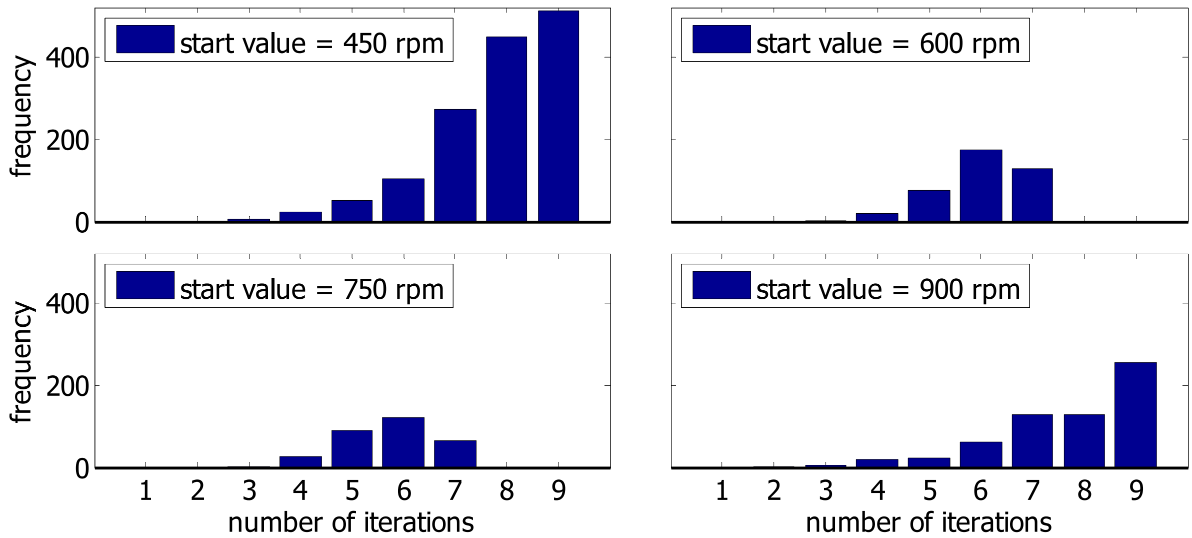



*Figure (6.10)* Frequency of number of iterations for different start values and positive initial search direction.

### 6.2.5 Discussion

The adaptive step size and direction of method D guarantees that the optimal value of the setting is found. In contrast, constant step sizes and a fixed search direction do not investigate the whole search space, and therefore do not necessarily find the absolute optimum. The adaptive step size revealed to be very efficient when settings are very badly adjusted. However, overshooting could be observed in many situations. When the first adjustment is too aggressive, the system needs more iterations to find the optimum. This is a problem, especially when starting from a setting which is close to the optimum. Users might be confused when step sizes are large and adjustments go back and forth. Overall, smaller maximum step sizes are more efficient. Due to varying sensitivities to setting changes for different crop types, crop dependent minimum and maximum step sizes have to be applied.

Section 6.2 is a theoretical analysis on the possible range of the number of iterations. Simulation was done over the entire physical range of the setting (example cylinder speed). In contrast, in the field, each crop type has a feasible range. The start value for optimization normally lies within this feasible range or not too far away from it. Cases like a start value of $450\ rpm$ cylinder speed and an optimal value of $1000\ rpm$ are not realistic in the field. Due to the conflicting quality parameters, cases with many succeeding iterations that have no influence on the quality parameters ($fbetter = 0$), or many succeeding iterations that result in permanently better quality ($fbetter = 1$), are also not realistic in the field. The results shown in this current section can be considered as a worst-case analysis.

## 6.3 Closed loop simulation

### 6.3.1 Combine model used for closed loop simulation

The closed loop simulations were executed using an adjustable combine model that was developed at the Chair of Agricultural Systems and Technology at TU Dresden. The combine model both represents the static and dynamic input-output behavior. The inputs to the model comprise the incoming grain and MOG mass flow, cylinder speed, concave clearance, chaffer and sieve opening, and fan speed. The outputs of the model are the combine quality parameters: separation, cleaning and threshing loss, grain damage, and the percentage of MOG and unthreshed material in the grain tank. The output threshing loss is not passed to the control algorithm because a corresponding sensor value can not be provided in a real environment. An output for straw quality is not provided by the combine model. As describe in chapter 5, straw quality is not considered as an objective for optimization in the automatic operating mode.

The dynamic behavior is modeled by transport delays and first order time delays. The static behavior is modeled by separation efficiencies of the different combine units. The separation efficiencies are a function of the incoming grain and MOG mass flow, cylinder speed, concave clearance, chaffer and sieve opening, and fan speed. An adaptation routine is applied to adapt the combine model so that it represents desired conditions. The conditions can be derived from measured data. Another way to modify the combine model is by use of an editor which offers the possibility to define two-dimensional relationships between input and output parameters of the model. Thus, the basis for the static input-output behavior of the adapted combine model are known quantitative relationships between input and output parameters. The model is valid for defined input ranges. Outside of these input ranges, the limits of the input ranges are utilized (no extrapolation). For further reading on the combine model see [117].

As the combine model requires grain and MOG throughput as input parameters, but the control algorithm uses forward speed as actuating parameter, the forward speed values provided by the control algorithm must be converted into corresponding grain and MOG throughputs. This is done with the assumption of a constant grain to MOG ratio, a constant yield, and a constant cutting width. The values utilized and the static input-output behavior of the combine model are shown in appendix A.2 and A.1.

The combine model and the adaptation routine were developed in parallel to the development of the control algorithms. Therefore, the combine model and adaptation routine could not be used as a part of the control algorithm. There is potential to use the combine model for a future control algorithm if it is possible to determine the quantitative input-output relationships online while harvesting.

### 6.3.2 Simulation procedure and definition of evaluation criteria

For closed loop simulation a set of initial settings has been defined. For each setting three different levels were used: a value 10% higher than the lower limit of the valid range, the center of the valid range, and a value 10% below the upper limit of the valid range. All possible combinations of the six settings forward speed, cylinder speed, threshing clearance, chaffer and sieve opening, and fan speed were generated. The total number of initial starting points is hence $number\_of\_levels^{\,number\_of\_settings} = 3^6 = 729$. Starting with these initial settings the control algorithm optimized the settings until satisfactory quality was reached or the amount of possible adjustments had been exhausted. Satisfactory quality was defined by the thresholds listed in table 6.2. The return flow volume is used exclusively in combination with other thresholds. The control algorithm does not start an optimization run if the return flow volume is the only output parameter which exceeds its threshold (see also chapter 5).

The thresholds were defined according to common quality standards. The 1% total loss level is said to be the economic optimum [32]. Lower loss can be achieved by lower throughputs which lead to higher production costs due to longer machine operation times and unfavorable engine operating points. The typical distribution between separation and cleaning loss is 2:1. Grain quality standards are defined for example in the guidelines for intervention cereals of the European Union [118] or the Saxon

*Table (6.2)* Quality thresholds in [%] applied for closed loop simulation.

| return flow volume | separation loss | cleaning loss | damaged grain (grain tank) | MOG (grain tank) | unthreshed material (grain tank) |
|---|---|---|---|---|---|
| 10 | 0.7 | 0.3 | 2 | 2 | 1 |

guidelines for ecological cereal production [119]. In the guideline of the European Union the maximum permissible values for damaged grain for hard and soft wheat are 6% and 5%, respectively. The maximum permissible values for MOG are 5% and 7%, respectively. The Saxon guidelines for ecological cereal production defines a maximum permissible value of 2% for damaged grain and 2% for MOG. In general, cereal receiving points have different quality standards. As the goal of the control algorithm is quality optimization, the high standards of the Saxon guidelines for ecological cereal production have been chosen for closed loop simulation. A clear indication of the permitted percentage of unthreshed material is missing in the guideline. Unthreshed heads are sometimes considered as MOG. For simulation the threshold has been set to 1%.

The combine operator can specify priorities between quality parameter groups. For simulation two different priorities P1, P2 were applied (see table 6.3).

*Table (6.3)* Operator priorities applied for closed loop simulation.

| priority | losses | grain damage | cleanliness | straw quality |
|---|---|---|---|---|
| P1 | 1 | 2 | 3 | 4 |
| P2 | 3 | 1 | 2 | 4 |

The evaluation criteria used to analyze the simulation results are:

- the cost value that describes the overall combine quality, and derived characteristic values,
- the time that was needed to find a satisfactory solution (quality below threshold), and
- the final forward speed.

The cost value is a weighted sum of the quality parameters. The weights (see table 6.4) are defined according to the operator priorities from table 6.3. The characteristic parameters that are derived from the average costs of different cases are explained in table 6.5.

*Table (6.4)* Weights applied to determine the total cost for a combination of quality parameters.

| weights | separation loss | cleaning loss | damaged grain | MOG | unthr. material |
|---|---|---|---|---|---|
| W1 | 3 | 3 | 2 | 1 | 1 |
| W2 | 1 | 1 | 3 | 2 | 2 |

*Table (6.5)* Characteristic parameters for evaluation of simulation results.

| characteristic parameter | description |
|---|---|
| $r\_active$ | percentage of initial setting combinations which resulted in activation of the control algorithm (issue(s) present) compared to the total number of initial starting points (N=729) |
| $r\_resolved$ | percentage of issues that could be resolved compared to the number of initial setting combinations that resulted in activation of the control algorithm |
| $p\_improve\_active$ | percentage of improvement compared to initial settings; all data samples with active control are taken into consideration |
| $p\_improve\_rslvd$ | percentage of improvement compared to initial settings; all data samples with resolved issues are taken into consideration |
| $p\_improve\_setexh$ | percentage of improvement compared to initial settings; all data samples where the settings were exhausted and the issue(s) could not be resolved are taken into consideration |

The parameters $p\_improve\_active$, $p\_improve\_rslvd$ and $p\_improve\_setexh$ are calculated based on the average cost values $Favg$ of the corresponding data samples (formula 6.1).

$$p\_improve\_i = \frac{Favg\_init - Favg\_opt}{Favg\_init} \cdot 100\% \tag{6.1}$$

### 6.3.3 Simulation results

The simulation has been run with the two different conditions shown in appendix A.3 and each condition with the two different priorities from table 6.3. For each of these four configurations forward speed has both been used as a constant and a variable setting.

#### 6.3.3.1 Results for standard conditions

Figure 6.11 shows the histogram of the costs before and after optimization for all utilized initial settings in standard conditions. The left plot shows the costs for the initial settings. The right plot shows the costs after optimization. A clear shift to lower costs can be seen which means an improvement of the combine quality. The worst cost of the optimized settings is about half the worst cost of the initial settings. However, a cost value higher than $Fcost = 7$ means that the issue(s) could not be resolved. When all quality parameters are exactly at their thresholds (table 6.2), then the cost value is $Fcost = 7$. The histograms for the other priority and forward speed configurations can be found in the appendix.

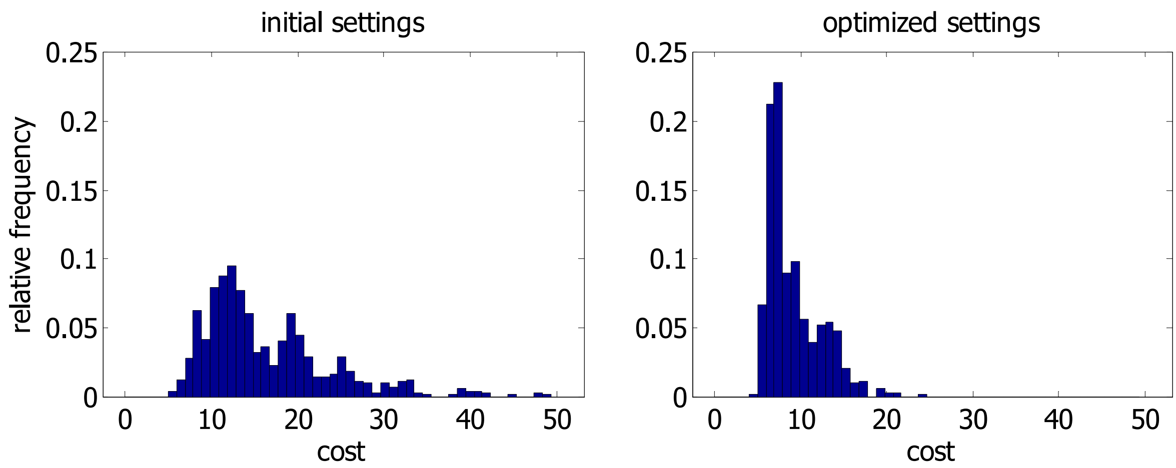



*Figure (6.11)* Histogram of cost values for standard conditions (C1), priority P1 and constant forward speed.

The high percentage of active control ($98.1\%$) shows that the conditions C1 are very difficult (see table 6.6). Due to the difficult conditions, the percentage of issues resolved lies between $27.0 - 31.3\%$. This is fairly low. More improvement was achieved using priority P1. Thus, conditions C1 allow better optimization towards grain loss than towards grain quality. Within the priority groups the percentage of issues resolved hardly depends on the variability of forward speed.

*Table (6.6)* Standard conditions (C1): Improvements in [%] achieved by the control algorithm.

| | priority P1 | | priority P2 | |
|---|---|---|---|---|
| | forward speed | | forward speed | |
| | constant | variable | constant | variable |
| *r_active* | 98.1 | 98.1 | 98.1 | 98.1 |
| *r_resolved* | 27.8 | 31.3 | 27.0 | 30.9 |
| *p_improve_active* | 44.4 | 44.6 | 35.1 | 34.5 |
| *p_improve_rslvd* | 46.6 | 48.2 | 37.4 | 36.8 |
| *p_improve_setexh* | 43.8 | 43.4 | 34.3 | 33.5 |

*Table (6.7)* Standard conditions (C1): Machine adjustment times to reach optimum settings [min] for priority P1 and (P2).

| | mean | | minimum | | maximum | |
|---|---|---|---|---|---|---|
| | fwd. sp. | | fwd. sp. | | fwd. sp. | |
| | const. | var. | const. | var. | const. | var. |
| control active | 10.0 (9.4) | 11.3 (11.1) | 0.7 | 0.7 | 18.5 | 21.2 |
| issues resolved | 5.7 (5.8) | 6.6 (6.7) | 0.7 | 0.7 | 17.8 | 19.9 |
| settings exhausted | 11.6 (11.2) | 13.5 (13.0) | 4.9 | 6.2 | 18.5 | 21.2 |

The machine adjustment times are higher when forward speed is variable (table 6.7). The combine model that represents conditions C1 does not comprise interaction effects between settings. An adjustment of a specific setting does not influence the impact of the other settings on the combine quality parameters. Thus, the use of forward speed as a variable setting simply means that one more setting is adjusted, which requires more time. When the adjustment direction is negative, forward speed is the last setting that is used. The differences between priority P1 and P2 are marginal.

Table 6.8 shows the final forward speeds for conditions C1. The final forward speeds for the configuration with constant forward speed are equal to the minimum, maximum and average values of the initial forward speeds. The average and maximum final forward speeds do not differ between the constant and variable speed configuration. The differences between the final forward speeds for priority P1 and P2 are marginal. The minimum final forward speed when forward speed was variable lies between $1.4-$

*Table (6.8)* Standard conditions (C1): Final forward speed [kph] for priority P1 and (P2).

| | mean | | minimum | | maximum | |
|---|---|---|---|---|---|---|
| | fwd. sp. | | fwd. sp. | | fwd. sp. | |
| | const. | var. | const. | var. | const. | var. |
| control active | 4.0 | 3.9 | 2.8 | 1.4 | 5.1 | 5.1 |
| issues resolved | 3.1 | 3.1 | 2.8 | 2.2 (1.8) | 4.0 | 4.0 |
| settings exhausted | 4.3 | 4.3 | 2.8 | 1.4 | 5.1 | 5.1 |

$2.2\ kph$. These are unacceptably low values. However, this might be a problem of the combine model. The model is valid in a certain range (see section A.1). Outside of this range the output values at the limits of the valid range are applied. For the control algorithm this means that the feedback from the model is equivalent to "no change". The control algorithm then makes more adjustments in the same direction. After the feedback "no change" has occurred three times, the algorithm stops adjusting the current setting and proceeds with adjusting a different setting. In a real application the valid range is equivalent to the physical range of the settings. The case "no change" would occur rarely, if at all.

#### 6.3.3.2 Results for dry conditions

*Table (6.9)* Dry conditions (C2): Improvements in [%] achieved by the control algorithm.

| | priority P1 | | priority P2 | |
|---|---|---|---|---|
| | forward speed | | forward speed | |
| | constant | variable | constant | variable |
| $r\_active$ | 72.0 | 72.0 | 72.0 | 72.0 |
| $r\_resolved$ | 53.7 | 53.7 | 53.7 | 53.7 |
| $p\_improve\_active$ | 41.5 | 67.6 | 41.2 | 67.1 |
| $p\_improve\_rslvd$ | 53.2 | 56.1 | 52.4 | 55.1 |
| $p\_improve\_setexh$ | 38.3 | 70.7 | 38.2 | 70.4 |

With conditions C2 $72\%$ of the initial settings resulted in non-satisfactory quality (issues present) (see table 6.9). The percentage of issues that could be resolved ($r\_resolved$)

is the same for all configurations. The average improvements achieved by the optimization ($p\_improve\_active$) are higher when forward speed is variable. There is slightly more improvement when forward speed is variable when considering only the cases where the issues could be resolved ($p\_improve\_rslvd$). There is significantly more improvement when considering the cases where the issues could not be resolved ($p\_improve\_setexh$). The differences between the characteristic values for priority P1 and P2 are marginal.

*Table (6.10)* Dry conditions (C2): Machine adjustment times to reach optimum settings [min] for priority P1 and P2.

| | mean | | minimum | | maximum | |
|---|---|---|---|---|---|---|
| | fwd. sp. | | fwd. sp. | | fwd. sp. | |
| | const. | var. | const. | var. | const. | var. |
| control active | 15.6 | 10.1 | 0.7 | 0.7 | 26.7 | 15.1 |
| issues resolved | 9.2 | 7.2 | 0.7 | 0.7 | 20.6 | 13.7 |
| settings exhausted | 22.9 | 13.4 | 17.8 | 12.4 | 26.7 | 15.1 |

The machine adjustment times are shorter when forward speed is variable (table 6.10). The adjustment of forward speed brings the combine to a more favorable operating point because the utilized combine model for conditions C2 represents interactions between input parameters. Subsequent adjustments of the other settings are either more efficient or not necessary at all. Thus, the total number of adjustments is lower and the simulation time is shorter. The minimum simulation time of $0.7\ min$ corresponds to a single adjustment. The machine adjustment times for priorities P1 and P2 are exactly the same. The combine model for conditions C2 shows much higher sensitivity against losses than against grain quality (see figure A.2 in the appendix). With priority P2 grain quality has a higher rank. Settings which improve grain quality are used first. However, as the improvement of grain quality has a fairly low magnitude, the overall combine quality does not improve much. In order to improve the overall combine quality, the grain losses must be reduced, no matter what the priority is.

The final forward speeds in table 6.11 for the configuration with constant forward speed are the minimum, maximum and average values of the initial forward speeds. The mean value reflects that combine quality gets worse with increasing throughput (here forward speed and throughput are equivalent because a constant grain to MOG ratio and cutting width were applied). When the issues could be resolved, there are marginal differences between the final forward speeds for the variable and constant forward speed configurations. The final forward speeds are lower for the cases where the issues could not be resolved. Lower forward speed means lower throughput and

*Table (6.11)* Dry conditions (C2): Final forward speed [kph] for priorities P1 and P2.

| | mean | | minimum | | maximum | |
|---|---|---|---|---|---|---|
| | fwd. sp. | | fwd. sp. | | fwd. sp. | |
| | const. | var. | const. | var. | const. | var. |
| control active | 4.1 | 3.8 | 2.9 | 2.9 | 4.7 | 4.3 |
| issues resolved | 3.6 | 3.5 | 2.9 | 2.9 | 3.8 | 3.8 |
| settings exhausted | 4.7 | 4.1 | 4.7 | 3.9 | 4.7 | 4.3 |

hence less productivity. However, the improvement in quality achieved with a variable forward speed is $67\%$ instead of $41\%$ for constant forward speed. The simulation results make clear the tradeoff between harvest quality and productivity. The combination of harvest quality and productivity (throughput) determines the harvest performance. A decision whether to prefer constant or variable forward speed cannot be made without utilizing the throughput as an additional objective for optimization. The results for the case “control active” are a combination of the results of the cases “issues resolved” and “settings exhausted”. According to the individual results of “issues resolved” and “settings exhausted”, the average final forward speed is lower when forward speed is used as a variable parameter.

### 6.3.4 Discussion

The percentage of issues that could be resolved is between $27.0\%$ and $53.7\%$. This number strongly depends on the conditions and the thresholds. A better indicator for the improvement is the relation between the cost value of the initial and the optimized settings ($p\_improve\_active$, $p\_improve\_rslvd$, $p\_improve\_setexh$). The average improvement is between $34.5\%$ and $67.6\%$ which shows the good performance of the control algorithm.

The optimization algorithm stops as soon as all quality parameters are below their thresholds. This approach has been selected to keep the machine adjustment time as short as possible. In addition to that, this is the way operators normally set up their machine. From the histograms (see figure 6.11 and the appendix A.3) it can be concluded that the maximum machine potential is not utilized. The minimum cost value in the histograms indicates a possible global optimum of the combine quality. In order to reach a global optimum, the current threshold based (or issue based) approach must be replaced by the objective “Find the absolute minimum of the cost value”. The application of this objective is only feasible if the input-output-behavior of the combine is known quantitatively in a sufficiently large input range. This was not given during the development of the control algorithm, due to lack of sensors for grain quality. However, work is done in this area which makes a global approach feasible in the near future.

For closed loop simulation a combine model has been used that represents the ideal behavior between settings (as inputs) and quality parameters (as outputs). Sensor noise, yield variations and variations in the internal process chain have not been considered. However, these effects do not directly influence the algorithm for *Setting Adjustment Determination*. Noise and process variation have an impact on the *Issue Detection* (see 5.3) and the *Steady State Detection*. The *Issue Detection* algorithm works with a filter and with tolerances to handle noise and process variation. The *Steady State Detection* suspends setting adjustments if the process is not in a steady state. The minimum time between two adjustments is 30 sec. The delay time between two adjustments in the simulation was always 30 sec because the combine model is free from disturbances, . This is the ideal case. In reality, the actual delay times are longer due to process variation and logistic actions like headland turn, reentering crop after a headland turn, and waiting for a trailer for unloading. The maximum simulation time of $26.7\ min$ is rather long and will be even longer in a real application in the field. In the interactive operating mode (operator evaluates quality and provides the feedback for the algorithm) this fairly long optimization time might not be acceptable. The operator might quit the optimization before a satisfactory operating point could be found. In the automatic operating mode (control algorithm runs in the background; feedback is provided by sensors) long optimization times may be more acceptable. Long optimization times will mainly occur in the first optimization run on a new field when the initial settings are far from the optimal settings. Subsequent optimization runs will terminate in a shorter time, assuming that conditions change gradually and not drastically within the same field.

A negative characteristic of the combine model is that it is valid in a defined input range which is smaller than the actual physical range of the settings. If the settings that are recommended by the control algorithm are outside of the valid input range, the model outputs at the limits of the range are held. The feedback from the model to the control algorithm is then equal to “no change”. This requires additional iterations which increase the simulation time. In a real application the feedback “no change” does not occur as often as in the simulation due to the likelihood of conflicts between quality parameters. The number of iterations, and hence the optimization time, is expected to be lower in the field. Nevertheless, the iterative approach of the optimization algorithm means a deficiency with respect to optimization time.

As throughput is not considered an objective for optimization, forward speed should be constant. Otherwise, there is the risk that a reduction of forward speed leads to an unacceptable decrease in throughput, which means a decrease in overall combine performance.

## 6.4 Conclusions

In simulation, the average improvement from initial settings to optimized settings is between 34.5 % and 67.6 %. This shows the good performance of the control algorithm. The results also show that the maximum potential is not utilized. The minimum cost value in the histograms indicates a possible global optimum of the combine quality. In order to reach a global optimum, the current threshold based (or issue based) approach must be replaced by the objective “Find the absolute minimum of the cost value”. The application of this objective is only feasible if the input-output-behavior of the combine is known quantitatively in a sufficiently large input range. This was not given during the development of the control algorithm, due to lack of sensors for grain quality.

As throughput is not considered as an objective for optimization, forward speed should be constant. Otherwise, there is the risk that a reduction of forward speed leads to an unacceptable decrease in throughput, which means a decrease in overall combine performance.

The current chapter comprises a statistical analysis of the behavior and performance of the control algorithm for optimizing combine processes. A comparable analysis in field conditions requires several years of testing and tremendous effort. In order to assess the actual combine quality, loss and grain samples have to be taken in each test run. The number of different conditions is higher in the field, and hence more representative than the two conditions utilized for simulation. However, it is not possible to test such a high number of different initial settings (N=729) in the same constant conditions in the field. Such scenarios are only realizable in simulation. This emphasizes the need for the combination of the different evaluation methods simulation and field test.

Usability of the system in the interactive operating mode plays an important role for the efficiency of the control system. Usability can be evaluated in the laboratory to a certain extent. However, it is not possible to exactly reproduce the workload that is generated by real field conditions. It makes a huge difference if the operator can focus on process optimization and harvest performance, or if process optimization is one task among others which have higher priorities (see section 2.2.1). Final evaluation of usability must be done in the field.

A comprehensive evaluation of the control algorithm requires simulation results, field test results from the development phase and operator feedback of several years. The latter is not yet available.

# 7 Summary and outlook

## 7.1 Summary

Combine harvesters are subject to a variety of requirements, like high throughput, low grain loss, low damage of clean grain, high grain tank cleanliness, optimal straw quality and distribution. It is necessary to optimize the threshing and separation processes inside the combine. The only way to optimize these processes during harvest is to adjust the combine settings to existing conditions. However, finding the optimal settings is a challenging task, due to the huge number of influencing factors and the complexity of the harvest process. If settings are not adjusted properly, performance is wasted. The divergence of performance between experienced and inexperienced combine operators emphasizes the need for a control system that optimizes harvest efficiency based on the existing combine technology.

Permanent monitoring and control of harvest efficiency can only be reached by an automatic control system. The adjustment of combine settings has to be done in the background, keeping operator interactions at a minimum. However, for reasons of traceability, for gaining operator's confidence, and due to lack of sensor information, the approach of this thesis is a combined development of an interactive and an automatic control system.

A standard approach for development of control systems is to use a model on the given process. A considerable number of models on threshing and separation processes have been developed over the past decades. However, a model that can serve as a basis for a control system for process optimization must meet the requirements that

- all parameters that determine harvest quality are represented as model outputs,
- all relevant combine settings are represented explicitly, and that
- all model parameters are known.

Such a model does not exist. The development of models for threshing and separation processes is in general very time consuming and therefore not relevant for this work. In addition, an analytical model on combine processes will always contain a set of abstract model parameters that incorporate the impacts of the large variety of influencing factors. Online process identification is the only method to automatically adjust abstract model parameters to existing conditions. Within this work, these efforts are considered as too time consuming. An alternative is to use the comprehensive qualitative model given by [67, 68]. The model consists of direct correlations between all relevant combine settings and all crucial quality parameters. This model (see figure 3.3) is the only one that is relevant for the development of a control system with feasible effort and within feasible time. As the model does not contain a problem oriented representation, there is the need to enhance the model by existing expert knowledge on process optimization.

The optimization of combine processes is a multi-dimensional and a multi-objective optimization problem. The objectives of the optimization are the harvest quality parameters (grain losses, grain damage, grain cleanliness, straw quality). There are numerous classical methods to solve optimization problems. For the given optimization problem there exists no analytical objective function (no comprehensive analytical model). Hence, optimization methods that use derivatives can not be applied. In the interactive operating mode, only relative evaluation ("worse", "same", "better") will be provided by the operator. The number of function evaluations that a human can handle is very limited. Therefore, function evaluations must be kept to a minimum. Due to the high number of function evaluations when using direct search algorithms for multi-dimensional problems, such algorithms are not applicable. The Golden Section algorithm is the only suitable standard optimization method because it is based of a comparison of only two function values. However, this algorithm is only applicable for one-dimensional optimization problems. Alternative optimization methods that handle multi-dimensional and multi-objective optimization problems can be found in the domain of Artificial Intelligence. Expert knowledge on combine process optimization is available, and is suitable for use in a control system. The expert knowledge can be used in a heuristic search algorithm. Uninformed search techniques are inefficient with respect to the number of iterations and are therefore not relevant. Due to reasons of transparency, methods that apply random rules, like GAs, are also not suitable for the given optimization problem.

The objectives of the optimization are the harvest quality parameters (grain losses, grain damage, grain cleanliness, straw quality). In addition to that, throughput is a crucial factor for the overall combine performance. However, operators have their preferred forward speed; the speed at which they feel comfortable. Therefore, throughput is not considered as an objective for optimization. The decision variables, the parameters that can be modified, are the combine settings. A requirement of the control system is that it works both as an interactive assistance system and an automatic control system. This requirement brings the restriction that the only parameters that can be used for control are those that are automatically adjustable while harvesting. Hence, the decision variables of the control system are the following combine settings: forward speed, rotor/ cylinder speed, threshing clearance, chaffer opening, sieve opening and fan speed.

The development of a control system for optimizing combine processes comprised the following two major work packages:

- Acquisition of existing expert knowledge on combine process optimization as an enhancement to the existing qualitative model.
- Development of a control algorithm that uses the acquired expert knowledge and that is suitable for both an interactive and an automatic operating mode.

In this work, knowledge acquisition has been performed in order to obtain expert knowledge on combine process optimization. The result is a knowledge base with six adjustment matrices for different crop and combine types. The adjustment matrices contain problem oriented setting adjustment recommendations in order to solve single issues with quality parameters. A control algorithm has been developed that is also capable of solving multiple issues at the same time, utilizing the acquired expert knowledge. The basic principle to solve the given multi-objective optimization problem is a transformation into multiple one-dimensional single-objective optimization problems which are solved iteratively. Several methods have been developed that are applied sequentially.

In simulation, the average improvement from initial settings to optimized settings achieved by the control algorithm, is between 34.5 % and 67.6 %. This shows the good performance of the control algorithm. The results also show that the maximum machine potential is not utilized. The minimum cost value in the histograms indicates a possible global optimum of the combine quality. The current threshold based (or issue based) approach aims to achieve operator satisfaction. Due to the rather slow dynamics of the threshing and separation processes, optimizing these processes is in general time consuming. A requirement of the control algorithm was therefore to keep the number of setting changes at a minimum. Taking this requirement into account, a threshold based approach is most suitable as long as there exists no quantitative model on the input-output-behavior of the combine.

## 7.2 Outlook

With current sensor developments a comprehensive combine model which represents the quantitative input-output-behavior could become feasible in the near future. System identification routines would be necessary in order to adjust model parameters to existing conditions. System identification would require targeted setting changes in order to obtain a suitable data set training the model. The accuracy of the identified model would strongly depend on the capability of sensors for measuring harvest quality parameters. If a model is developed that represents the actual threshing and separation characteristics, standard optimization methods (see chapter 4.1) would become applicable. The optimization routine would run in the background, without additional setting changes in order to obtain the corresponding function values. Function values would be provided by the model. Compared to the current solution, less time would be necessary until an optimal combination of settings would be found. Tests have shown that interactions between settings play an important role. The iterative adjustment of single settings does not take these interactions into account. Optimization based on a quantitative model would be able to consider also interaction effects between settings.

Apart from settings that can be adjusted from the cabin, there are out-of-cab settings which require the operator to leave the cabin in order to make adjustments. If out-of-cab settings are not adjusted properly, the control algorithm for optimizing combine processes will have little success. A diagnostic system that detects mis-adjustments of out-of-cab settings is desirable.

Throughput is a crucial factor for overall combine performance. In a next stage of the control system, throughput should be added to the objectives. Losses, grain damage and grain cleanliness are easy to compare with each other because they all have the same unit (%). A suitable measure for the objective ’throughput’ has to be defined so that it is comparable with the already existing objectives.

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# A Appendix

## A.1 Combine model

### A.1.1 Standard conditions

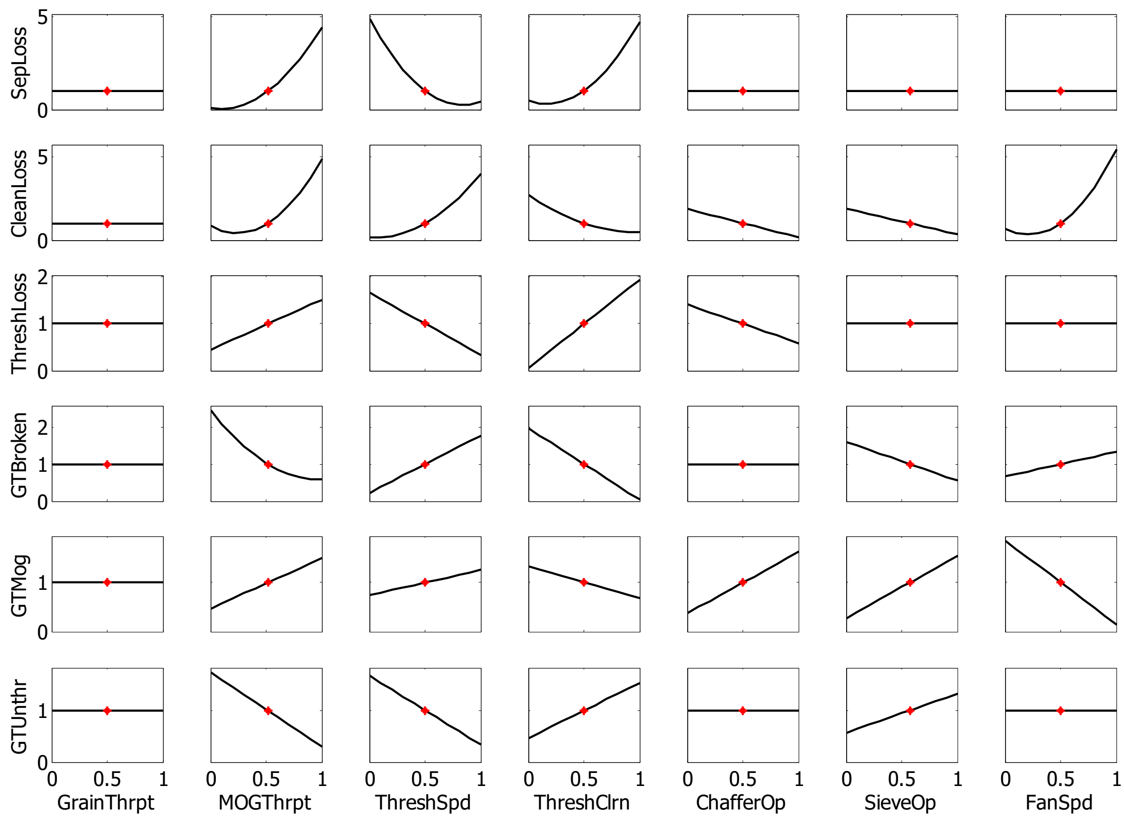


*Figure (A.1)* Normalized characteristics for standard conditions (C1). Reference quality: SepLoss = 0.5%, CleanLoss = 0.2%, ThreshLoss = 0.3%, GTBroken = 1%, GTMog = 1%, GTUnthr = 0.5%.

The characteristic curves of standard conditions (C1) were generated with an editor.

They are based on empirical knowledge. Figure A.1 shows the set of correlations between one input and one output with the condition that all other input parameters are at their reference values (marked with a red dot). Interactions of input parameters are not represented by the combine model due to lack of knowledge. The valid ranges of the input parameters are listed in table A.1.

*Table (A.1)* Valid ranges of input parameters for standard conditions (C1).

| input parameter | unit | min | max |
|---|---|---|---|
| grain throughput | t/h | 15 | 35 |
| MOG throughput | t/h | 12 | 45 |
| threshing speed | rpm | 750 | 1000 |
| threshing clearance | mm | 2 | 16 |
| chaffer opening | mm | 12 | 20 |
| sieve opening | mm | 5 | 12 |
| fan speed | rpm | 800 | 1200 |

### A.1.2 Dry conditions

The characteristic curves for dry conditions (C2) were derived from measured data. Threshing loss and the amount of unthreshed material in the grain tank were not measured. Therefore, the model does not provide the correlations between the input parameters and the two mentioned outputs. Threshing loss and unthreshed material in the grain tank are assumed to be zero. Figure A.2 shows the set of correlations between one input and one output with the condition that all other input parameters are at their reference values (marked with a red dot). Interactions of input parameters also represented by the combine model, however, they are not shown in figure A.2.

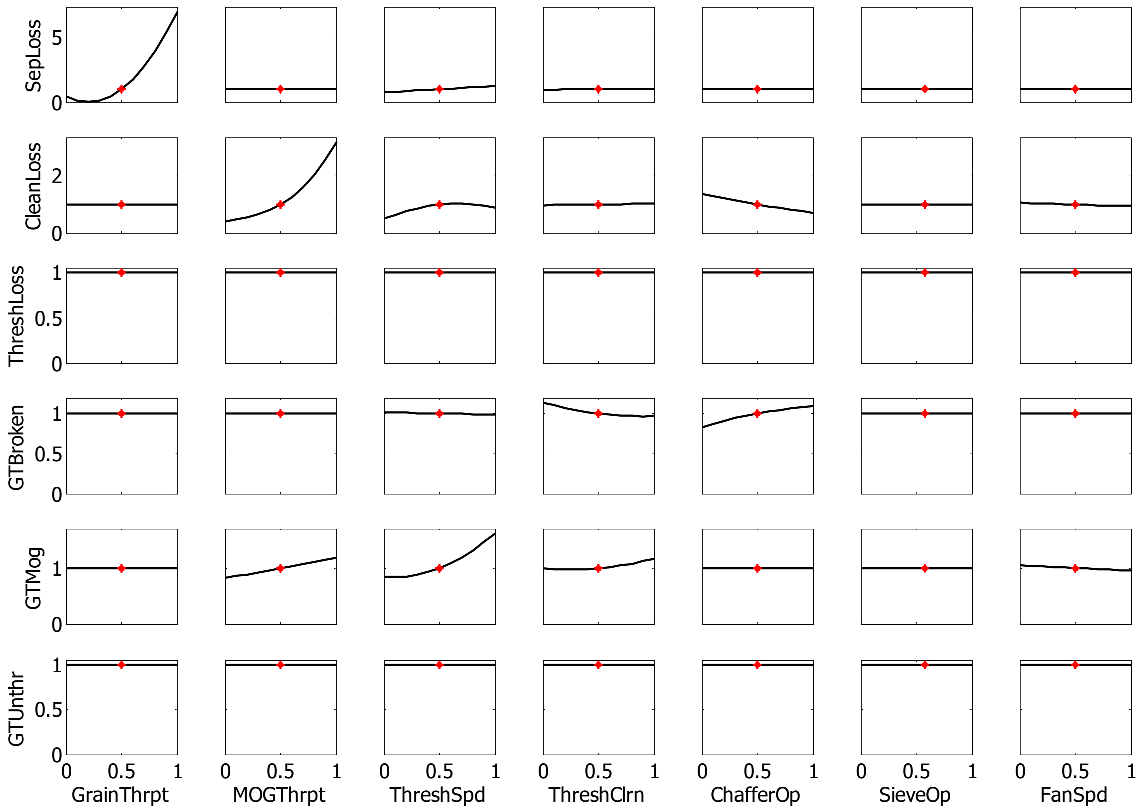


*Figure (A.2)* Normalized characteristics for dry conditions (C2). Reference quality: SepLoss = 0.48%, CleanLoss = 0.81%, ThreshLoss = 0%, GTBroken = 0.003%, GTMog = 0.005%, GTUnthr = 0%.

*Table (A.2)* Valid ranges of input parameters for dry conditions (C2).

| input parameter | unit | min | max |
|---|---|---|---|
| grain throughput | t/h | 15 | 35 |
| MOG throughput | t/h | 20 | 40 |
| threshing speed | rpm | 800 | 1000 |
| threshing clearance | mm | 2 | 20 |
| chaffer opening | mm | 14 | 18 |
| sieve opening | mm | 3 | 10 |
| fan speed | rpm | 800 | 1100 |

## A.2 Simulation parameters for closed loop simulation

- grain to MOG ratio: 0.8
- yield: 7 t/ha
- cutting width: 9 m

## A.3 Simulation results - histograms

### A.3.1 Standard conditions

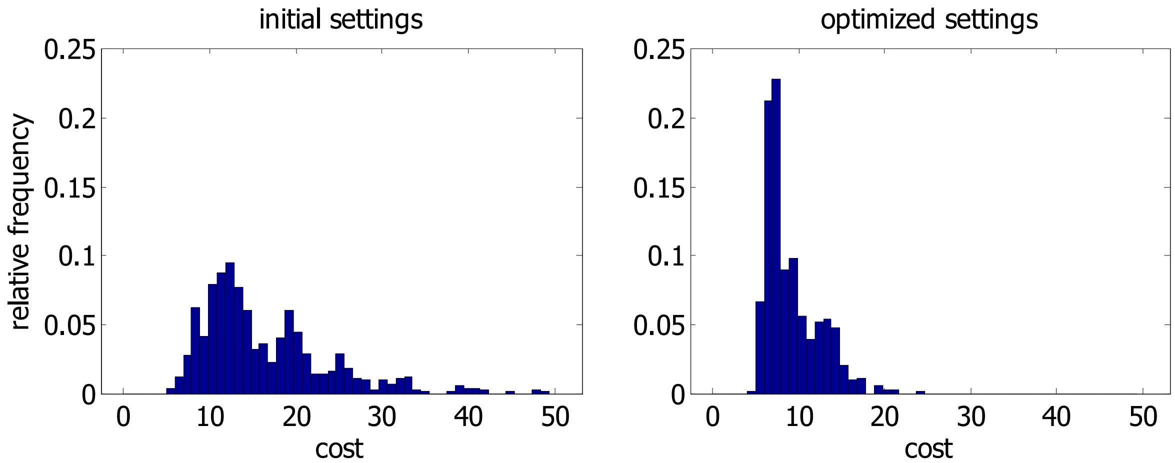


*Figure (A.3)* Histogram of cost values for standard conditions (C1), priority P1 and constant forward speed.

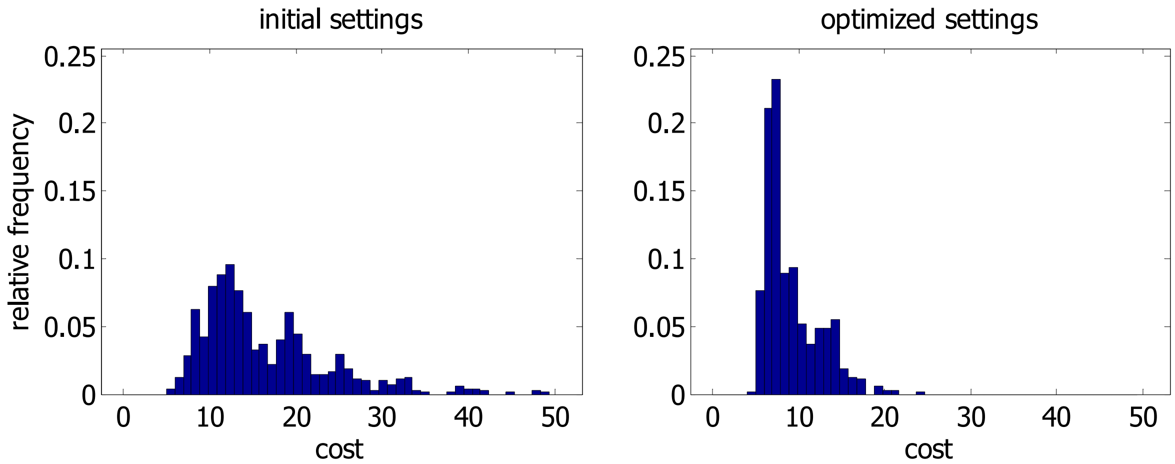


*Figure (A.4)* Histogram of cost values for standard conditions (C1), priority P1 and variable forward speed.

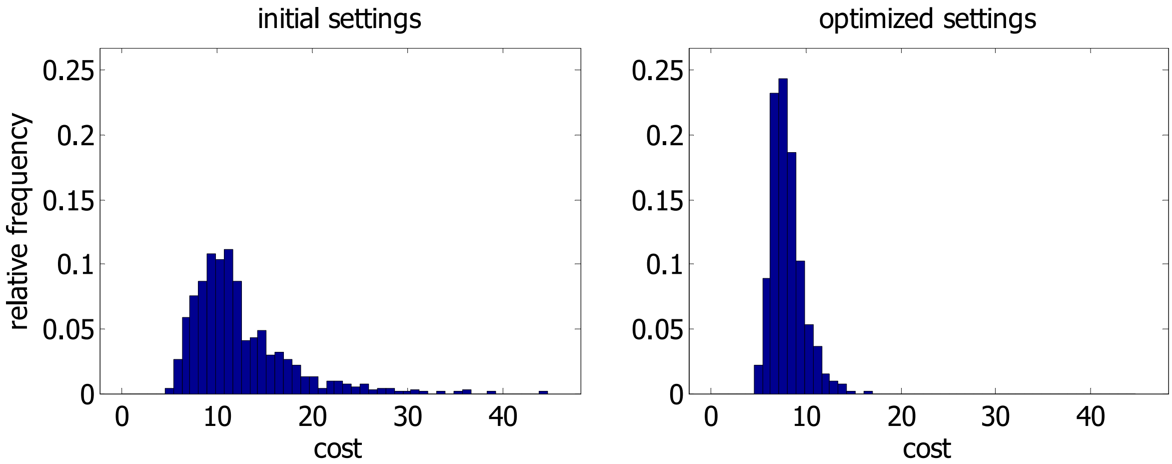


*Figure (A.5)* Histogram of cost values for standard conditions (C1), priority P2 and constant forward speed.

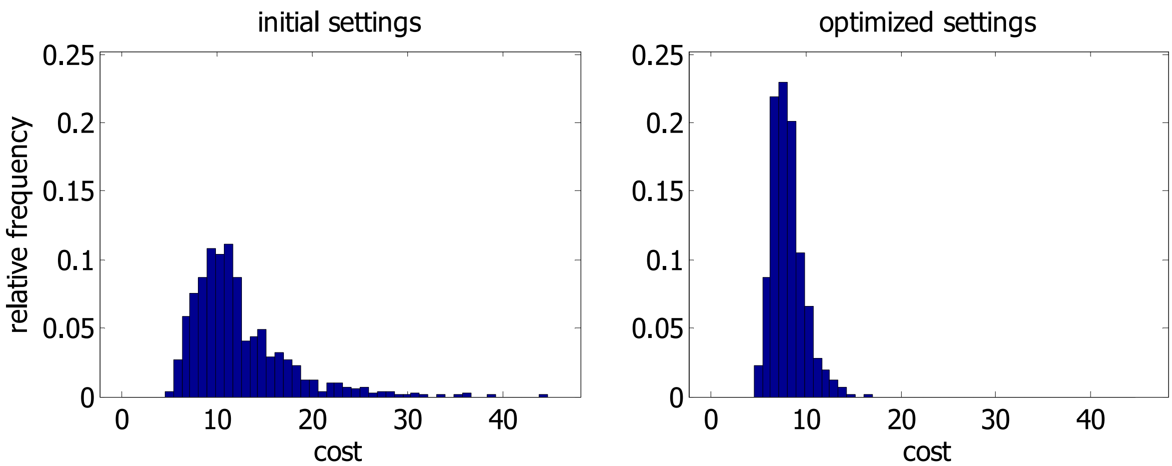


*Figure (A.6)* Histogram of cost values for standard conditions (C1), priority P2 and variable forward speed.

## A.3.2 Dry conditions

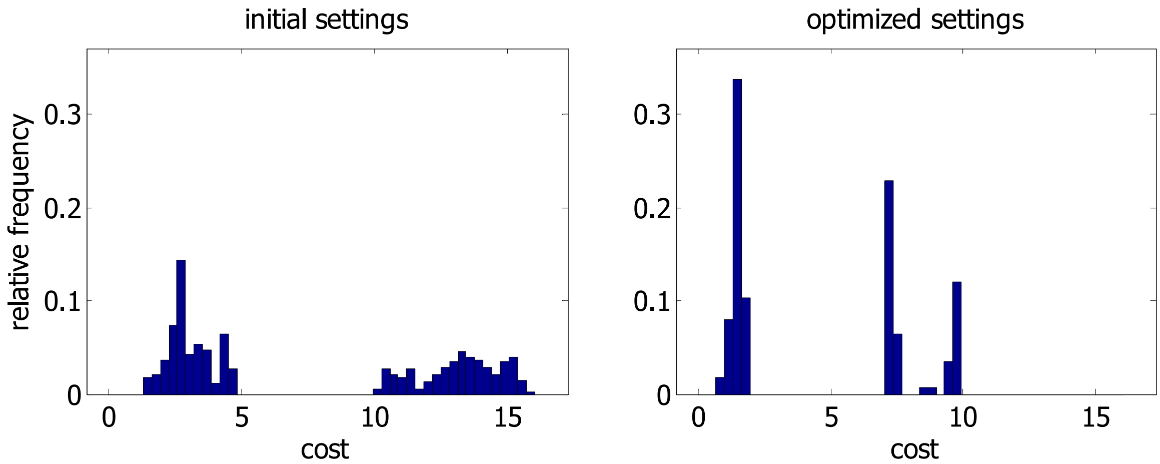


*Figure (A.7)* Histogram of cost values for dry conditions (C2), priority P1 and constant forward speed.

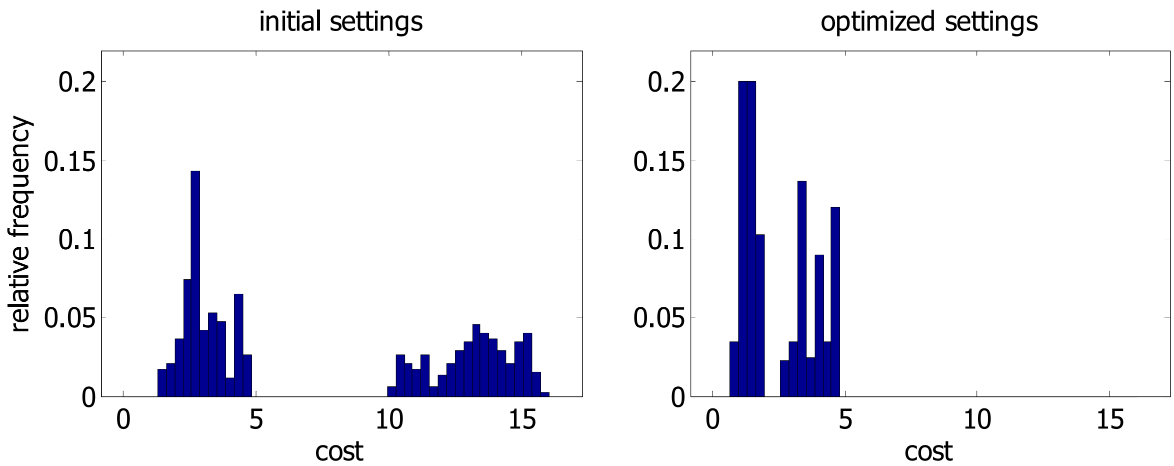


*Figure (A.8)* Histogram of cost values for dry conditions (C2), priority P1 and variable forward speed.

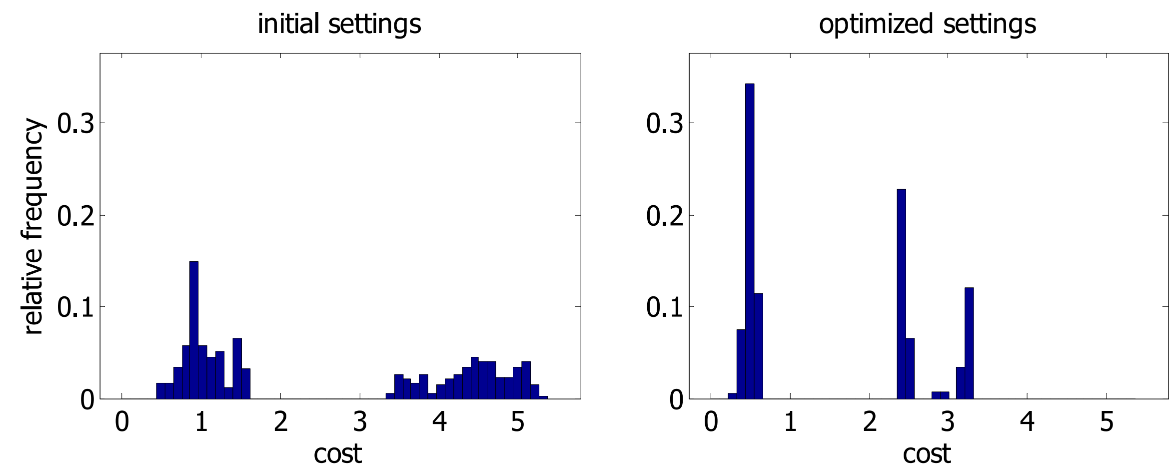


*Figure (A.9)* Histogram of cost values for conditions C2, priority P2 and constant forward speed.

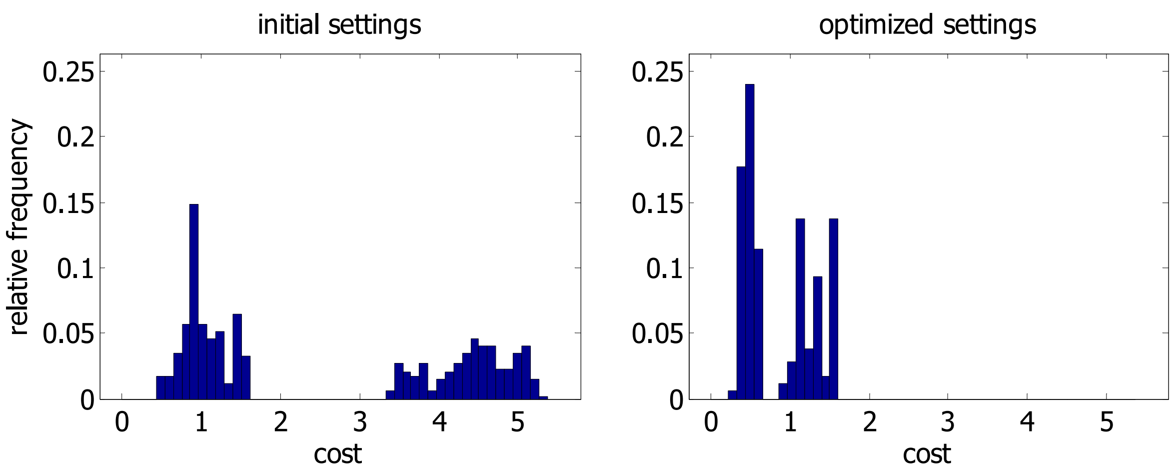


*Figure (A.10)* Histogram of cost values for dry conditions (C2), priority P2 and variable forward speed.