



Manufacturing Management and Decision Support using Simulation- based Multi-Objective Optimisation

Leif Pehrsson

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Abstract

Abstract

A majority of the established automotive manufacturers are under severe competitive pressure and their long term economic sustainability is threatened. In particular the transformation towards more CO₂-efficient energy sources is a huge financial burden for an already investment capital intensive industry. In addition existing operations urgently need rapid improvement and even more critical is the development of highly productive, efficient and sustainable manufacturing solutions for new and updated products. Simultaneously, a number of severe drawbacks with current improvement methods for industrial production systems have been identified. In summary, variation is not considered sufficient with current analysis methods, tools used are insufficient for revealing enough knowledge to support decisions, procedures for finding optimal solutions are not considered, and information about bottlenecks is often required, but no accurate methods for the identification of bottlenecks are used in practice, because they do not normally generate any improvement actions. Current methods follow a trial-and-error pattern instead of a proactive approach. Decisions are often made directly on the basis of raw static historical data without an awareness of optimal alternatives and their effects. These issues could most likely lead to inadequate production solutions, low effectiveness, and high costs, resulting in poor competitiveness. In order to address the shortcomings of existing methods, a methodology and framework for manufacturing management decision support using simulation-based multi-objective optimisation is proposed. The framework incorporates modelling and the optimisation of production systems, costs, and sustainability. Decision support is created through the extraction of knowledge from optimised data. A novel method and algorithm for the detection of constraints and bottlenecks is proposed as part of the framework. This enables optimal improvement activities with ranking in order of importance can be sought. The new method can achieve a higher improvement rate, when applied to industrial improvement situations, compared to the well-established shifting bottleneck technique. A number of “laboratory” experiments and real-world industrial applications have been conducted in

order to explore, develop, and verify the proposed framework. The identified gaps can be addressed with the proposed methodology. By using simulation-based methods, stochastic behaviour and variability is taken into account and knowledge for the creation of decision support is gathered through post-optimality analysis. Several conflicting objectives can be considered simultaneously through the application of multi-objective optimisation, while objectives related to running cost, investments and other sustainability parameters can be included through the use of the new cost and sustainability models introduced. Experiments and tests have been undertaken and have shown that the proposed framework can assist the creation of manufacturing management decision support and that such a methodology can contribute significantly to regaining profitability when applied within the automotive industry. It can be concluded that a proof-of-concept has been rigorously established for the application of the proposed framework on real-world industrial decision-making, in a manufacturing management context.

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Skövde, September 2013

Leif Pehrsson

Declaration

I declare that the work described within this thesis was originally undertaken by me, (Leif Pehrsson) between the dates of registration for a degree of Doctor of Philosophy at De Montfort University.

Declaration

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List of Acronyms and Abbreviations

3D	Three-dimensional
4D	Four-dimensional
ABC	Activity Based Costing
AGV	Automatic Guided Vehicle
AT	Available Time
CO ₂	Carbon Dioxide
DES	Discrete Event Simulation
DoE	Design of Experiments
EMA	Environmental Management Accounting
EMO	Evolutionary Multi-objective Optimisation
FACTS	Factory Analysis in ConcepTual phases using Simulation
GA	Genetic Algorithms
IDSS	Intelligent Decision-Support System
IFA	International Federation of Accountants
Innovization	<u>Innovation through Optimisation</u>
JPH	Jobs Per Hour
LHS	Latin Hypercube Sampling
LM	Loss Model
MDT	Mean Down Time
MOO	Multi-Objective Optimisation
MTM	Methods Times Measurement
MTTR	Mean Time To Repair
OEE	Overall Equipment Effectiveness
PC	Parallel Coordinate

List of Acronyms and Abbreviations

PDCA	Plan, Do, Check, Act
PIAB	Professional Accountants In Business
PrOACT	Problem, Objective, Alternatives, Consequences, Trade-offs
SBI	Simulation-Based Innovization
SCORE	Simulation-based CONstraint REMoval
SBO	Simulation-Based Optimisation
SMO	Simulation-based Multi-objective Optimisation
SSA	Six Sigma Academy
ToC	Theory of Constraints
TPM	Total Productive Maintenance
TPS	Toyota Production System
VSM	Value Stream Mapping
WIP	Work in Process or Work in Progress
WL	Work Load

Notation

\hat{A}	= Two level constraint removal parameter for availability
α	= Work cell or station cycle time
$\hat{\alpha}$	= Constraint removal state for work cell or station cycle time
β	= Work cell or station availability (up time)
$\hat{\beta}$	= Constraint removal state for work cell or station availability (up time)
Bc	= Buffer Capacity
\hat{C}	= Two level constraint removal parameter for cycle time
γ	= Work cell or station mean downtime
$\hat{\gamma}$	= Constraint removal state for work cell or station mean down time.
\hat{D}	= Two level constraint removal parameter for mean down time
$\Delta\xi$	= Incremental cost
$\Delta\xi_A$	= Incremental annual cost
$\Delta\xi_C$	= Custom cost component
$\Delta\xi_S$	= Incremental sustainability cost
$\Delta\xi_T$	= Incremental cost related to throughput
$\Delta\xi_U$	= Incremental cost per unit
$\Delta\rho$	= Incremental sustainability performance
ε	= Energy consumption
ε_A	= Annual energy consumption
ε_H	= High energy consumption (working)
ε_I	= Initial energy consumption
ε_L	= Low energy consumption (idling)

ε_S	= Stand by energy consumption
λ	= Investment (improvement cost)
λ_B	= Investment (Buffer related)
λ_C	= Custom investment component
λ_P	= Investment (processing time related)
λ_S	= Sustainability investment
λ_U	= Investment (availability and up time related)
μ	= Material consumption with corresponding expressions
v_A	= Annual production volume
ξ_{FE}	= Energy cost factor
ξ_H	= Cost per hour
$\bar{\xi}_H$	= Average cost per hour
ξ_I	= Initial cost
ξ_m	= Incremental maintenance cost
ξ_R	= Annual running cost
ρ_A	= Annual sustainability performance
ρ_I	= Initial sustainability performance
τ	= Incremental production time
τ_A	= Required production time
τ_I	= Initial production time
φ	= Throughput
φ_I	= Initial throughput
ω	= Waste with corresponding expressions

Chapter 1.

Introduction

This Chapter describes the background and motivation for the research presented in the thesis, based on the industrial situation and current scientific trends. The scope of the research and its objectives are defined and followed by a brief description of the hypothesis, proposing a framework for decision support based on SBO and post optimality analysis. Subsequently, a short review of research methods, including an introduction to and motivation for the ones used, is presented. Finally, the organisation of the thesis is described to guide the reader through its contents.

1.1 Background

The long-term economic sustainability of a majority among incumbent automobile manufacturers is threatened (Zapata and Nieuwenhuis, 2009). Many established companies within the automotive industry are under severe pressure from emerging competition and the total automotive production capacity available is larger than the market demand (KPMG, 2012). The current, repetitive financial crises have highlighted severe profitability weaknesses of many companies in the United States (U.S.), especially with regard to the Big Three Automakers, despite productivity improvements. The North American Harbour Report from 2008, which was the last one with officially reported figures, revealed a wide profitability gap between Japanese and American automotive manufacturer for their North American sales. In some cases, companies offer promotions to increase sales, advertise new products, or in order to reduce their inventories (Demirag et al., 2011), of which the automotive industry in the U.S. is mentioned as an example. The crisis is not isolated to American companies and

several European manufacturers are in severe trouble, of which one recent example is SAAB Automobile, the Swedish car manufacturer that filed for bankruptcy twice before it was closed down. Other examples are Opel and Peugeot, figuring in many news articles (e.g., in Financial Times) concerning profitability problems. According to Zapata and Nieuwenhuis, (2009) “the mass production automobile is characterised by the all-steel body and petrol-fuelled internal combustion engines”. They conclude that this leads to a trap in which each competitor must sell a large number of vehicles to reach a break-even point, since the companies are constrained by considerable capital investments. The already high, capital intensive systems within the automotive industry are likely to lead to resistance regarding new energy sources (powertrains) that require further capital. Meanwhile, the automotive industry is in a phase of adapting to more CO₂-efficient powertrains and vehicles, with an industrial system that needs to be modified accordingly. The profitability trend within automotive industry can be summarised as in Figure 1.1.

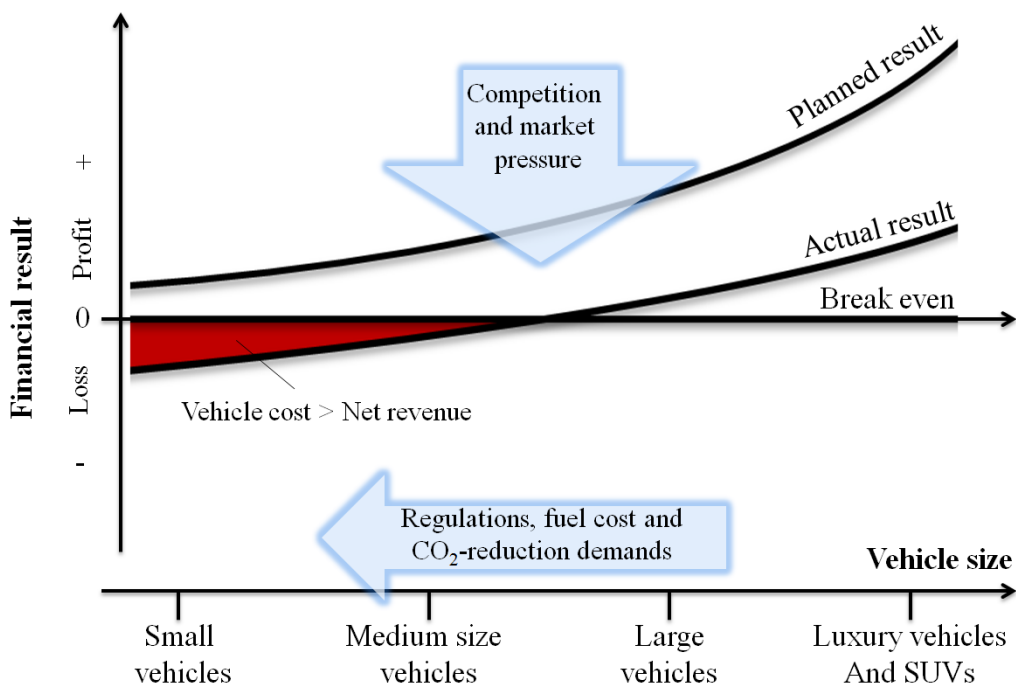


Figure 1.1 Profitability trend within the automotive industry (modified from a confidential source).

New products, components, and a growing number of variants are being introduced into the industrial systems, which necessitate major re-configuring and change-over of the manufacturing operations. The industry's profitability largely depends on decisions in the concept and design phases of production facilities and manufacturing operations, since a very considerable proportion of investments and operational costs are locked early in a products or a production systems lifecycle. Improvement activities in current production operations are simply not enough and other measures must already be taken in the early life cycle phases. Although current operations must run smoothly and efficiently, and while there are many benefits from improvement strategies and industrial methods, such as Lean and Six Sigma, many decisions about production systems are based entirely on experience from existing processes and estimation tools that do not take variation into account. Often, data is collected, saved, and available in large quantities within industry today, providing the prerequisites for very detailed analyses of existing processes. The tools used are mostly for static analysis of historical data and not used dynamically to identify the effects of parameter changes on a system. Hence, the full potential of this asset is seldom utilised for decision-making in the conceptual development, as well as design and improvement phases of production systems. Instead, decision makers very often experience the so-called data haystack syndrome (Goldratt, 1991), when they try to find relevant information in the huge amount of data, illustrated in Figure 1.2.

1.2 Deficiencies of current management methods and tools

There are a number of management methods and improvement principles for manufacturing operations, such as Lean, Six Sigma, Theory of Constraints (ToC), Factory Physics, with various tools attached. The industry often relies on lean methods to solve production issues; however, lean is a necessary but insufficient approach for analysing production system issues (Standridge and Marvel, 2006). According to Rother (2010), the Toyota Kata methodology will produce superior results. There are, however, some severe drawbacks with the Kata improvement concepts, such as the step by step exploration of improvements, which omit the opportunities of exploring scenarios,

concepts, and obstacles in advance. Hence, it is a reactive instead of a proactive method, risking the excessive use of improvement recourses, due to the lack of planned activities.

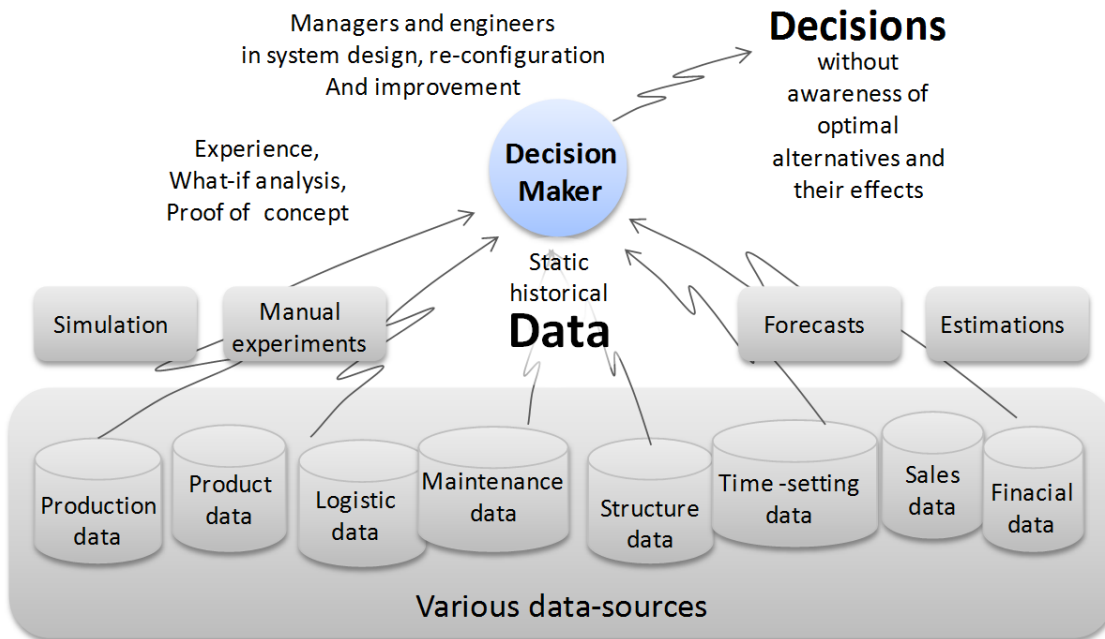


Figure 1.2. Current industrial practice in decision-making for system design, re-configuration, and improvement.

Value Stream Mapping (VSM) takes the complete process perspective; it promotes flow and changing the process from batch oriented into something resembling a Toyota Factory (Rother, 2010). However, there are some serious shortcomings with VSM; it does not take variability into account and is limited to a single product variant.

Six Sigma can be used to reduce variations, but it does not take the complete production system perspective into account. According to Ha (2005), Six Sigma tools cannot be used effectively without a thorough understanding of statistics and the assumptions made from each tool. In addition, there is a serious risk that wrong decisions will be made due to incorrect analyses of data and the misinterpretation of results. In particular, within Six Sigma, Design of Experiments (DoE) is the main tool for the exploration of

the most influencing factors and their correlations, in order to optimise the process under study. Nevertheless, this is yet another complicated tool requiring specialist knowledge in order to be able to produce adequate information useful for decision-making. It is possible to use DoE to optimise the process, e.g., using response surface, but this requires even more in-depth statistical knowledge and skills to carry out the task.

On the other hand, ToC promotes the improvement of a system's constraint (bottleneck) which restrains the performance of the entire system. Thanks to ToC, this observance of locating the single weakest link of a system, in order to improve the overall throughput, is now accepted in industrial practices. However, the main weakness of ToC is that it does not provide any exact methods for finding the constraint. It can become a repetitive improvement cycle that goes from solving one constraint to another, making it much like the Toyota Kata approach – in terms of the inability to foresee the next improvement step until the former has been implemented.

Factory Physics, defined by Wallace and Spearman (2008) as “a systematic description of the underlying behaviour of manufacturing systems”, is based on a set of principles defined through mathematical expressions and equations such as Little's Law, worst-case performance and practical worst-case performance. The degradable effect of variability on a system's performance is one essential principle recognised within Factory Physics. The “laws” identified in Factory Physics have provided very useful insights into the behaviour of various concepts for production systems. However, since most of these insights are derived from queuing theories, the use of Factory Physics for deeper analysis of complicated real-world factories could be limited by the modelling capability of queuing models.

In terms of modelling, simulation is a tool that can be used to provide decision support throughout the life-cycle of a production system, from conceptual design to maintenance (De Vin, et al., 2004). It is accepted as the only general purpose and generally applicable modelling tool for truly complex systems (Fu et al., 2000). It is

even claimed in Tempelmeier (2003) that if quantitative performance evaluation is carried out at all in industry, “then in almost any case simulation is the only tool used”. On the other hand, there are also studies showing that the manufacturing industry has not been entirely successful in using simulation as a decision-support tool, despite the fact that it holds tremendous promise and possesses a strong and established background (McNally and Heavey, 2004). It is believed there are three main reasons:

- (1) A lack of knowledge, skills and time for the development of simulation models – decision makers involved in the upstream decision-making hierarchy seldom possess the time or required skills to build models and must, in many cases, rely on consultant firms or simulation experts, which would cause longer lead time and higher cost in a production system development process.
- (2) Simulation by itself does not provide optimised solutions – as an evaluative modelling method, simulation is not truly an optimisation tool (AlDurgham and Barghash, 2008), and a significant amount of time is usually needed in the experiment and analysis phase, particularly if the aim is to find the optimal parameter setting for the problem.
- (3) Similarly, but with a slightly different purpose, simulation alone does not generate patterns of systems so that higher-level knowledge to support decision-making can be acquired. The skills and time required with which to conduct experiments and analyses, in order to draw conclusions from the simulation model, are seldom affordable for most decision makers.

Since timely decisions have to be made in various phases of the production system development process, all such factors that prolong the process of using simulation for decision support would be unacceptable. Altogether, these reasons may explain why manufacturing industry is less successful in using simulation as a decision-support tool, as concluded in McNally and Heavey (2004). The common industrial practice is therefore to develop simulation models to verify decisions that have already been made and investment costs that have almost been determined, rather than proactively exploring more promising alternatives prior to the decision-making.

1.3 A new scientific trend

The theory behind this thesis is that for simulation to be effectively used to support decision-making in manufacturing management, some new optimisation technologies and data analysis procedures have to be explored and developed in addition to simulation models for production systems. Such a theory is formed partially on the basis of the argument made in Tolio et al., (2010) that simulation models need to be coupled to external analysis procedures that generate patterns of systems with modified parameters whose performance has to be evaluated to find the best changes. However, it is also related to the new scientific trend that has emerged in computational intelligence, namely, the integration of multi-objective optimisation (MOO) and advanced data analysis techniques for discovering knowledge that cannot easily be done by other approaches. The idea of deciphering knowledge by performing post-optimality analysis on Pareto-optimal solutions generated from MOO was first introduced by Deb (2003). He coined the term, *innovization*, meaning discovering innovative principles via optimisation, to show the uniqueness of this approach. Originally, only visual means of analysing the solutions through two-dimensional plots between variables, objectives, and constraints were used. Later, regression techniques were added to discover the mathematical correlations among these entities (Deb and Srinivasan, 2006). By using data mining techniques, innovization has subsequently extended to become an automated procedure to reveal several analytical relationships simultaneously, for engineering problems with higher dimensions (Bandaru and Deb, 2011).

So far, the innovization concept has mostly been applied to problems related to engineering design issues. By integrating the concept of innovization with discrete-event simulation, it is believed that a new set of powerful tools can be developed for general systems analysis, particularly suitable for production systems development. Such an idea of integrating simulation-based multi-objective optimisation (SMO) with innovization is called Simulation-based Innovization (SBI), as found in Ng et al.,

(2009), Dudas et al., (2011), and Ng et al., (2011). Although related work in SBI has shown that useful knowledge related to common performance measures, such as throughput, work in process (WIP), and lead time, can be extracted to support decision-making, it is argued that the method has to be extended to incorporate financial and sustainability parameters and objectives, if it is to address real-world manufacturing management problems.

1.4 Research aim and objectives

Based on the above-mentioned theory, the aim of this research is to define a new framework and explore its essential components, including any methods, techniques, models, and algorithms, so that production simulation models can effectively be used to support decision-making in production systems development and improvement. As discussed above, for such a decision support framework to create an impact on solving real-world manufacturing management problems, it has to not only take productivity parameters and objectives into account, but also financial and sustainability ones. In other words, defining the integration of SMO with productivity, financial, and sustainability parameters and objectives is also a special focus of this research. Additional objectives to achieve the overall aim of this research are listed below:

1. A comprehensive state-of-the-art review of a wide variety of topics, from industrial improvement methods, manufacturing accounting to computational intelligence, in order to acquire a general understanding regarding which components are essential for integration into the framework.
2. Formulation of new cost and sustainability models, suitable for integration into simulation models, so that multiple objectives related to different aspects in manufacturing management can be computed and analysed by the optimisation and data analysis procedures.

3. Development of new innovative methods/algorithms for identifying bottlenecks in production systems, as well as extracting knowledge to support decision-making activities in manufacturing management.
4. Extensively conduct “laboratory” experiments using test simulation models, both for the evaluation and demonstration of the data models, methods, and algorithms developed.
5. Apply the techniques and methods developed to industrial-based production system re-design and improvement projects to demonstrate and prove that the framework is both feasible and applicable for solving real-world manufacturing management problems.

1.5 The conceptual framework

The conceptual framework can be outlined on how decision-making support within manufacturing management for production systems development and improvement can be built on the theory of this thesis by modifying Figure 1.2 into Figure 1.3 below. By comparing Figures 1.2 and 1.3, there is a stark contrast between the knowledge-based decision support proposed in this thesis and the current data-intensive industrial practice. The foundation is a simulation model of the production system connected to SMO, with problem independent metaheuristic search methods incorporating general-purpose genetic algorithms (GA) that can be applied to a variety of MOO problems (Talbi, 2009). The addition of functions for running cost estimation and investment integration together with the modelling of sustainability parameters, such as energy consumption, material consumption and waste, opens opportunities to optimise a production system from a multi-disciplinary perspective. In combination with post-optimality analysis, these parameters meet industrial requirements on providing information for financial decision-making, favouring sustainable solutions within the design and improvement of production systems. For a production system, the objectives in a decision situation might include one or several of the following examples:

maximise throughput, minimise the system’s cycle time (leadtime), as well as WIP, the required number of buffers, the running cost, energy consumption, amount of investment, the number of palettes, or minimise the amount of resources required. These are just a few examples that provide some background on relevant objectives. In summary, the proposed framework shall provide a structure for the transformation of data into knowledge, supporting decision-making within manufacturing management and production systems design.

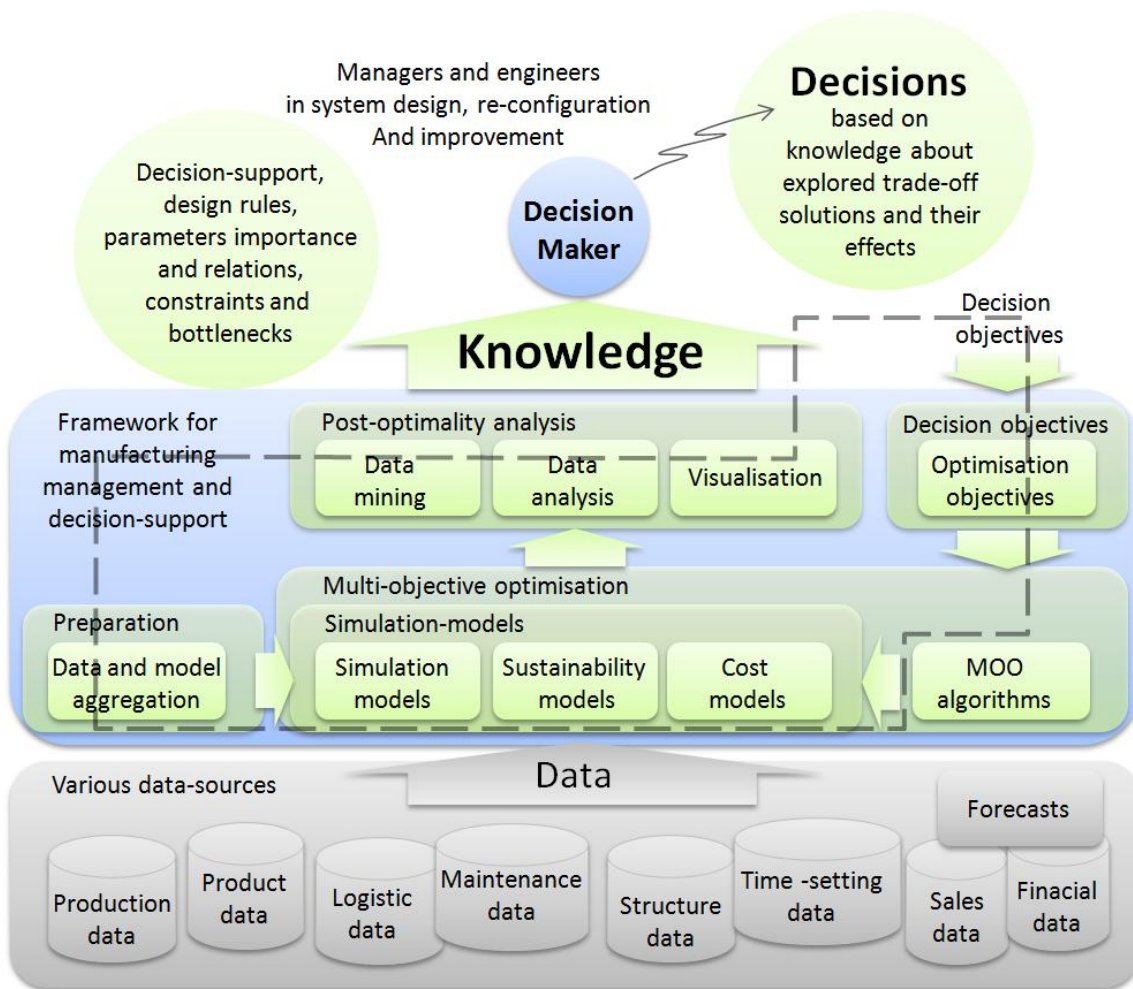


Figure 1.3. The proposed, general conceptual framework for manufacturing management and decision-support with specific contributions from this work included within the dashed line.

1.6 Scope

A new foundation for production system decision support is proposed by defining a procedure for enhancing the production system design process using SMO. Such a new SMO framework and method will induce the design of a new integrated toolset for production systems design and analysis. The design and partial implementation of this toolset is included in this study and applied to several industrial problems. The work has also generated a significant amount of data as well as analysis results, which are valuable both for industry and academics. This thesis contributes to illustrating not only the methodology, but also the analysis results of these industrial applications that are particularly carried out in the automotive industry. It is believed that such a methodology will be applicable to any discrete manufacturing systems for which discrete-event simulation models can readily be made. However, this thesis does not aim at addressing system-level problems related to continuous process industries producing non-discrete products, even though the concept of performing post-optimality analysis on SMO data from continuous simulation models may be applicable.

On the other hand, the framework and methodology introduced in this thesis shall naturally lead to the research of a new generation of intelligent decision-support systems (IDSS) which provide more advanced intelligent functions to assist the decision makers (Viademonte and Burstein, 2006). While systems development as a research methodology (see also Section 1.7) to partially develop the proposed methods and algorithms to demonstrate and prove the applicability of the framework is unavoidably needed, it is outside the scope of this thesis to provide a complete software architecture design and software development of such a new IDSS for production systems development (see also Chapter 10, Future work). In other words, research in this thesis is more of the type of “proof-of-concept” or “proof-by-demonstration” that is commonly used by management information systems researchers (Nunamaker et al., 1991).

Similarly, while it is, in principle, possible to embed post-optimality analysis into a MOO algorithm to enhance the optimisation efficiency, in terms of faster convergence to the preferred region of the decision maker (Ng et al., 2012), it is also outside the scope of the thesis to investigate some new high-performing MOO algorithms. In summary, the contributions aimed at in this thesis are focused on the areas included within the dashed line in Figure 1.3.

1.7 Research Methods

According to Blake (1978), research is “systematic intensive study directed toward fuller scientific knowledge of the subject studied”. Connected to knowledge, the branch of philosophy referred to as epistemology is “conceived as the theory of knowledge and justification” (Audi, 2011). Another philosophical belief system is ontology, dealing with what can be known and how. Starting from a philosophical standpoint, different perspectives about the meaning of truth and objective reality can be taken (Roth and Mehta, 2002) and, according to the positivist approach, there is “a true explanation or cause of an event”. Hence a hypothesis can be tested for verification (or rejection). Positivist science in combination with beliefs about the nature of knowledge will form positivist epistemology that is the cornerstone of the quantitative paradigm (Hesse-Biber and Leavy, 2011). The interpretivist approach, on the other hand, seeks to “unravel patterns of subjective understanding” and the truth is “shaped by the viewers’ perception and understanding of the world”. According to Roth and Mehta (2002), these approaches are not necessarily opposed to each other, but rather are different ways of viewing the same data. A more approximate form of positivism is post-positivism which relates to emerging elaborate scientific theories requiring more than direct conclusions from data with “facts not directly observed”, claiming a probability or level of objectivity rather than certainty (Crotty, 1998). According to Hesse-Biber and Leavy (2011), there are also critical approaches including postmodernism, post-structuralism, feminism, critical race theory, and queer theory. The critical approaches, which have

developed in multidisciplinary and interdisciplinary contexts, both value and evaluate experience, understanding, and subjectivity. Post-positivism, interpretivist and critical approaches can all be used within qualitative research (Hesse-Biber and Leavy, 2011).

Nunamaker et al., (1991) take the view that research follows the pattern of “problem, hypothesis, analysis, argument”, as illustrated in Figure 1.4.

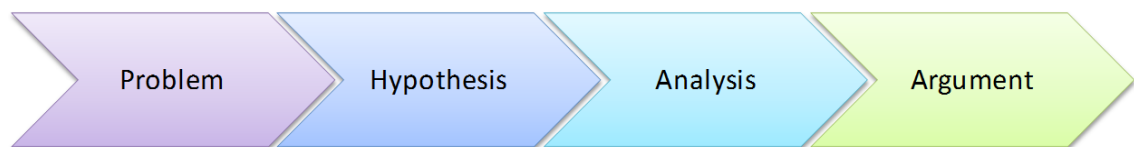


Figure 1.3. Research Pattern.

This positivist approach assumes that problems in the research domain, found by observation, are the basis for a hypothesis that analysis is attempting to confirm and generalise. The argument and the evidence defending the original hypothesis are the results of the analysis.

For many years, the basic choice that could be made regarding the research paradigm was between quantitative or qualitative, while nowadays there is a growing recognition of combined elements through multi-strategy design (Robson, 2011). According to Reswick (1994), the quantitative research process is linear, unidirectional and deductive, while qualitative research is inductive with iterative, or of a closed-loop feedback nature with comparative analysis. The research pattern described by Nunamaker (1991), Figure 1.4, mainly corresponds to the quantitative process with a hypothesis a priori to experiments and analysis. While the research presented in this thesis mainly follows the quantitative process, conclusions regarding the usefulness of the proposed framework are to some extent qualitative. The tests and experiments performed while evaluating the framework are mainly quantitative and data intensive, based on discrete event simulation (DES) models, MOO and data mining techniques. However, when the results from the application of the framework are considered as

knowledge and decision-support, the evaluation of how well it actually supports decision-making is qualitative.

According to Yin (2009), there are a number of research strategies, such as experiments, surveys, archival analysis, history, and case studies, which can be applied to the collection and analysis of empirical evidence (shown in Table 1.1).

Table 1.1. Conditions for research strategy selection (Yin, 2009).

<i>Method</i>	<i>Form of research question</i>	<i>Requires control of behavioural events</i>	<i>Focuses on contemporary events</i>
Experiment	How, why?	Yes	Yes
Survey	Who, what, where, how many, how much?	No	Yes
Archival Analysis	Who, what, where, how many, how much?	No	Yes/No
History	How, why?	No	No
Case Study	How, why?	No	Yes

A research strategy can be selected on the basis of three conditions, namely, “(a) the research question being posed, (b) the extent of control an investigator has over actual behavioural events, and (c) the degree of focus on contemporary as opposed to historical events” (Yin, 2009). The preferred strategies for a research question in the form of who, what, where, how many, or how much are surveys and archival analysis. With research questions of the type how and why, the strategies to be used are mainly experiments, histories or case studies. Regarding condition (b), only experiments relate to the requirement of control of behavioural events and, when considering condition (c), history obviously does not focus on contemporary events. Since the research presented in this thesis is mainly of the type that answers the how and why questions, the use of

surveys and archival analysis would have limited value and has not been applied. Using history as a strategy can also be excluded from the work, considering the focus on contemporary events. Control of behavioural events is required when applying optimisation on simulation models of production systems within the proposed framework. However, when the framework as a whole is evaluated, control of behavioural events might not be necessary. Hence, a combination of experiments and case studies could be used throughout the research.

The research mainly follows the pattern “problem, hypothesis, analysis and argument” through a multi-methodological approach comprising observation, theory building, experimentation, and framework development, as shown in Figure 1.5. There are many similarities to a multi-methodological approach, proposed by Nunamaker et al., (1991), for information systems research including observation, theory building, system development, and experimentation. A study (observation) of the deficiencies of existing management methods and tools, including simulation, was made in the early phases of this work. Theory building involves the outline of the conceptual framework and framework development is the realisation of verified procedures and methods in a context and a realised argument. As previously discussed, system development to partially implement the methods and algorithms designed must be carried out in order to test and measure the underlying framework and to demonstrate its feasibility and applicability. The idea of system development as a research methodology fits very well into the category of applied science which belongs to the engineering, developmental, and formulative types of research (Nunamaker et al., 1991). The developmental type of research involves the search, construction, or synthesis of instructions that yield a better course of action (Ackoff et al., 1962), which comfortably matches the goal of this thesis. The aim of formulative research is to identify problems for more precise investigations, as well as to gain insights that will increase familiarity with the problem area. In order to define the problem, a comprehensive literature review of the field of industrial improvement methods, providing a foundation of motivation for the research, was conducted. Then, subjects that could potentially be used to formulate the design of

the framework, such as innovization, SBO, MOO, cost models, accounting, cost management, environmental management, and decision-making, were studied.

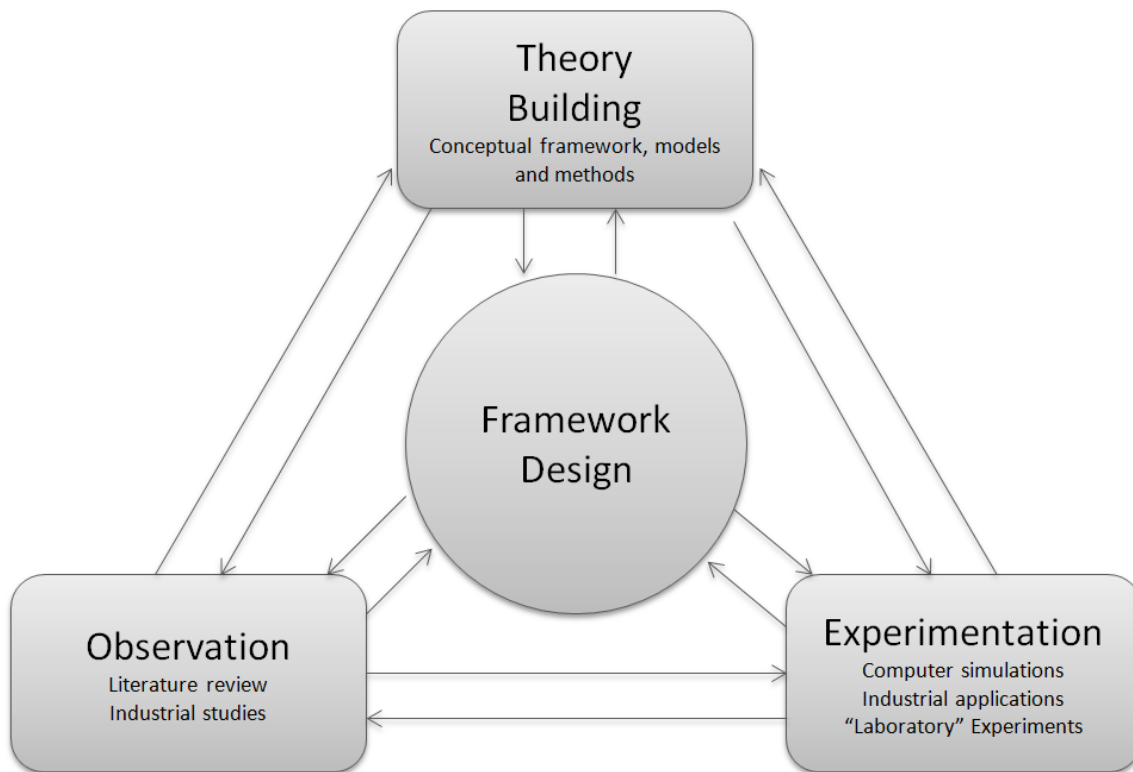


Figure 1.5. Multi-methodological research approach.

The design of a method and a framework for the application of MOO as a basis for decision support within production system development and improvement, including the development of cost- and sustainability-models, with the subsequent use of post optimality analysis, has been the most essential part of the research. Tests and validation in the analysis phase were carried out through a number of deductive, explanatory experiments (Perry, 1998; Yin, 2009). In order to answer testable hypotheses (Perry, 1998), individual well prepared “laboratory” experiments have been central to the scientific development (the term experiments used in analogy with what Flyvbjerg, (2006) concludes for case studies), through the opportunity to run an extensive number of iterations and replications within validated simulation environments. The proposal and the design of the framework were mainly performed a priori to the testing and the

experiments. Methods for post-optimality analysis have been explored, as part of the experiments, with regard to the possibilities for integration into the MOO procedures.

In order to promote validity, the strategy has been to apply triangulation (Robson, 2011) in the evaluation of the proposed framework. According to Denzin (2009), the four types of triangulation are data triangulation, investigator triangulation, theory triangulation and methodological triangulation. In an attempt to cover these as much as possible and striving for multiple triangulation (Denzin, 2009), the framework has been tested on both hypothetical setups and real-world problems, in different types of manufacturing operations with independent data sources and various decision situations involving different decision makers.

The research methods are mapped to the thesis structure, as illustrated in Figure 1.6.

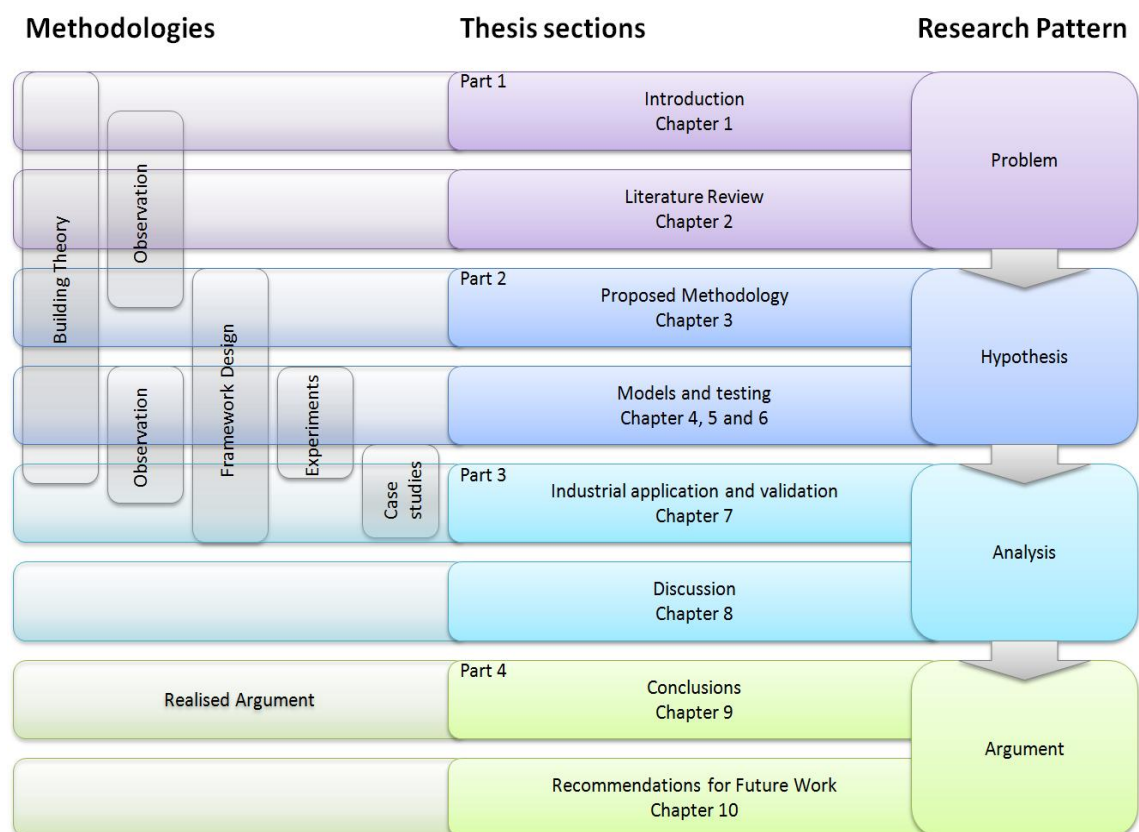


Figure 1.6. Research methods mapped to the thesis structure.

1.8 Thesis organisation

The thesis is organised as summarised below.

1.8.1 Chapter 1, Introduction

The background and motivation for the research is presented with objectives and the scope of the research. A brief description of the hypothesis with the proposed framework is given, followed by a review of research methods and motivation for the ones used. Finally, the thesis organisation is summarised.

1.8.2 Chapter 2, Literature review

Common industrial improvement paradigms and methods are analysed through a literature review, revealing some problems used as prerequisites for the formulation of the hypothesis in Chapter 3. The problems identified are further addressed in Chapters 4 to 6. However, the frame of reference is not limited to Chapter 2, since it actually starts with providing the background in Chapter 1 and continues in Chapters 3 to 6 and to some extent in Chapter 7 with topics specifically related to the subject of each chapter.

1.8.3 Chapter 3, A methodology for manufacturing Management using MOO

A framework supporting decision-making for production systems development and improvement is presented as a hypothesis to address the problems identified in Chapter 2. An additional literature review serves as foundation for the design of the framework. Some of the components required in order for the framework to support a wider range of decision situations are presented and tested in Chapters 4 to 6.

1.8.4 Chapter 4, Cost modelling including testing

A cost modelling approach for integration with the framework, introduced in Chapter 3, is proposed and tested through experiments. The literature review on cost modelling is a prerequisite for the design of the proposed cost modelling technique. Finally, some findings from the framework and the cost modelling experiments are presented.

1.8.5 Chapter 5, Sustainability modelling including testing

A sustainability modelling approach for integration with the framework, introduced in Chapter 3, and the cost modelling technique, introduced in Chapter 4, is proposed and tested. The literature review on sustainability is a prerequisite for the design of the proposed sustainability modelling technique. Finally, the findings from the test are presented.

1.8.6 Chapter 6, Bottleneck detection including testing

In order to address the drawback related to the identification of constraints and bottlenecks in production systems, touched upon in Chapter 1 and further identified in Chapter 2, a special application of the framework, proposed in Chapter 3, is presented and tested against an established, bottleneck detection technique.

1.8.7 Chapter 7, Industrial application and verification

The framework, proposed in Chapter 3, and the models, proposed in Chapters 4 to 6, are applied and verified by industrial field tests and industrial case studies. Through application to a variety of industrial problems, the opportunities that are opened by techniques for knowledge extraction are explored. The usefulness of the resulting decision support is evaluated. Each study provides separate findings that are also summarised at the conclusion of the Chapter.

1.8.8 Chapter 8, Discussion

The design of the framework, including the modelling techniques, its application and opportunities opened, and its limitations, is discussed in a broader context, with a few comments on related research. Some of the thoughts and insights obtained during the work on this thesis are shared.

1.8.9 Chapter 9, Conclusions

The overall conclusions are presented and related to the research objectives and the problems identified in Chapters 1 and 2. The findings in Chapters 4 to 7 are transformed and summarised into conclusions for the complete work.

1.8.10 Chapter 10, Recommendations for future work

Based on the findings and experience gained through the work presented in the thesis, recommendations for future work are presented.

Chapter 2.

Literature review

In this Chapter, common industrial improvement paradigms and methods are analysed through a literature review, revealing some problems with existing methods from which the research objectives, presented in Chapter 1, have been derived. The findings from the literature review are prerequisites for the formulation of the hypothesis and the proposal of a framework, in Chapter 3, addressing the identified shortcomings of existing methods. The frame of reference is not only limited to Chapter 2. In Chapter 1, the background to the research is presented on the basis of the financial situation within the automotive industry. Before the proposed framework is presented in Chapter 3, important background information is gained through a literature review. Likewise in Chapters 4 to 6, and to some extent in Chapter 7, topics specifically related to the subject of each Chapter are reviewed.

2.1 Lean production and Total Productive Maintenance

The huge success of the Japanese automotive manufacturers, with Toyota in the lead, has been studied at MIT and the term “Lean” was first used by Womack et al., (1990) to describe the concept and the production philosophy that has evolved from the Toyota Production System (TPS).

The expressions “lean production” or “lean manufacturing” are now widely spread within the manufacturing industry. The question is, however, how many have truly understood the philosophy based on TPS. In the foreword to *The Toyota Way* (Liker

2003), Gary Convis, a Managing Officer at Toyota and the President of Toyota Motor Manufacturing in Kentucky, summarises the Toyota way and TPS, which makes up the DNA of the company, into the two pillars that support it; “Continuous Improvement”, and “Respect for People”. He points out that they create an atmosphere of continuous learning that embraces change. Another definition by Radnor et al., (2011) is “a management practice based on the philosophy of continuously improving processes by either increasing customer value or reducing non-value adding activities, process variation, and poor work conditions”.

When viewed as an improvement methodology, the five essential steps in Lean, according to Nave (2002) are;

1. Identify which features create value.
2. Identify the sequence of activities called the value stream.
3. Make the activities flow.
4. Let the customer pull product or service through the process
5. Perfect the process.

The main theory of Lean is to remove waste in order to improve the flow. While the identification and removal of waste is a very strong focus, it can be argued that variability, as a major source of waste, is not adequately addressed due to the deterministic nature of Lean methods, even if variation is reduced as a secondary effect of process simplification. Both random and structural variations have to be tackled in order to improve the performance of any systems (Hopp and Wallace, 1998). TPS has been said to create a community of scientists, establishing a set of hypotheses that can be tested (Spear and Bowen, 1999). At the same time, Lean does not include any scientific methods or approaches for testing improvements and changes before implementation, in order to avoid sub-optimisation of systems. Despite a problem-solving process with detailed assessment of proposed changes, the implementation is based on trial and error from a system perspective. The ease of Lean’s acceptance within industry is, according to Ignizio (2009), due to its less scientific approach.

The following section of the review focuses on methods connected to production system analysis and flow analysis, namely; VSM, Total Productive Maintenance (TPM), and loss modelling. Subsequently, the improvement procedures, referred to as Kaizen and Kata, are discussed.

2.1.1 Value Stream Mapping

The VSM technique, derived from Toyota, and written down by Rother and Shook (1999), is a simple tool for analysing a manufacturing plant. Proceeding back from the customer and the finished goods, towards the supplier and the raw material, the current process is documented using pen and paper, during a line walk. The idea is to subsequently create a future state map that aims to reduce waste by creating a connected value stream and improving the flow through the plant. A few higher level objectives need to be considered when creating the current state map (Liker and Meier, 2005) and they include; flexible process that quickly responds to customer demand, short lead-time, connected processes with continuous flow and pull, separate flows for each value stream, simplified information flow, a so-called “pacesetter” or “pace maker” process within each value stream loop, and an awareness of customer requirements such as tact time (rate), required volume, mix, and sequence. Inventory is considered something to be questioned, and is seen as a reminder of the need to improve the process. One limitation of VSM is the danger that Lean is made to appear as easy as following a few steps in a methodology, while the reality is far more complex. Many skills are required to find the real improvements; it is not just a matter of drawing pictures. It seems like there is a wide gap between the theory and the actual level of real-world application (Serrano et al., 2008). Another downside of this method is its static, descriptive nature and its inability to analyse the true dynamic behaviour of the real system. Either the current state maps or the future state maps are able to include variability. The method does not capture the input parameters’ true influence on the overall system performance and no technique to find the system’s bottleneck has been included. It would, however, be possible to overcome some of these issues, by connecting or merging the value

stream map into a simulation model (Lian and Landeghem, 2007). Others, (Braglia et al., 2009), also consider that the disregard of real variability is a strong limitation of the method. They suggest alternatives, based on fuzzy algebra and statistics, to overcome this weakness.

2.1.2 Total Productive Maintenance, Loss Models, and Overall Equipment Effectiveness

Enterprises working with TPM sometimes employ a Loss Model (LM), in order to categorise how time and resources are utilised (Pehrsson, 2009, Nord and Petterson, 1997). The motivation to use a LM comes from the tasks of questioning activities and striving to use time and resources for value adding activities only. At the same time, energy and material consumption should be minimised. A common LM contains data that is required to calculate many of the key performance indicators used as decision support within production control and production management. Three main resource categories form a complete LM; 1) Utilisation of the production equipment and the total scheduled time, 2) The utilisation of man-hours, and 3) Utilisation of production resources. The first one contains the basis for the calculation of the LM's most essential key performance indicator, Overall Equipment Effectiveness (OEE) (Hansen, 2002). Each of the main categories is divided into a number of sub-categories. For the utilisation of production equipment and that of man-hours, the sub-categories are subsets of each other. The difference between the parent category and a subset category is considered a loss, as shown in Figure 2.1.

Through analysis of the losses, and sometimes further division into lower level loss subsets, the cause of the loss can be found, or at least an indication of what the cause might be.

Improvement of the OEE should be carried out according to ToC and Goldratt's critical chain (Goldratt, 1997), focusing on the factory's bottleneck assets. An improved OEE measure can then be linked to financial benefits, either by producing more products

(assuming that everything produced is sold) during a given production period, or by reducing the time required to manufacture the original amount of products (Hansen, 2002).

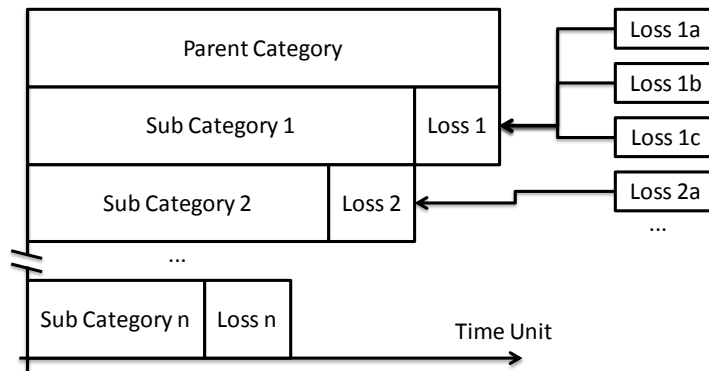


Figure 2.1. Loss model principle with subset categories.

LM or OEE strategies are actually not meant to identify constraints or bottlenecks. The purpose of a LM is to focus on reducing the use of production resources and the OEE is more of a measurement instrument. Hence, a bottleneck detection methodology is required, in order for an OEE improvement strategy to work properly.

2.1.3 Continuous Improvement (Kaizen), Kata and organisational learning

The traditional word for Lean's continuous improvement concept is Kaizen which is driven by reflection, the key to learning (Liker and Meier, 2005). The concept of learning through Kaizen is not possible without a foundation, based on standardised processes. The ideal standard is a tacit knowledge of how things should be done rather than just a documented process. The Kaizen concept is primarily intended for process improvements. Liker and Meier (2005) criticise the Kaizen workshop approach,

claiming it focuses too much on individual processes and on being too short term, instead of promoting flow across the enterprise.

A more recent concept is the Kata process, defined as “a repeating routine of establishing challenging target conditions, working step-by-step through obstacles (Improvement Kata), and teaching this to employees at every level to ensure it motivates their ways of thinking and acting (Coaching Kata)” (Rother, 2010). While the setup of target conditions is an important prerequisite for improvement, the actions required are explored on the way towards the target, which could be argued follows a trial and error process, without the capability to forecast the actions required. The way to the target is a gray zone, according to Rother (2010), Figure 2.2., who presents an analogy of a flashlight that only shines so far in the darkness, Figure 2.3. You have to take a step forward to see further in the darkness and spot obstacles.

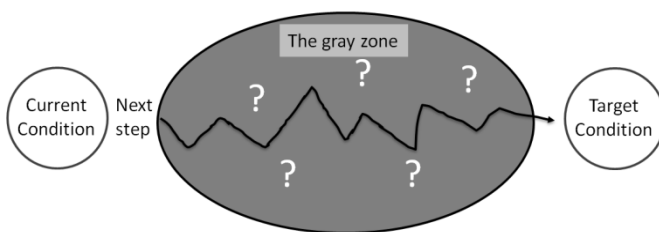


Figure 2.2. The Kata way to the target (Rother, 2010).

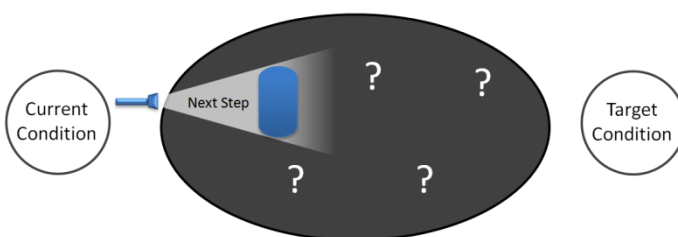


Figure 2.3. The Kata flashlight analogy (Rother, 2010).

The path to the target condition is believed to be beyond the limit of what can be predicted and it is assumed that exploring it is only possible by successive experiments. According to Rother (2010), by applying the Plan-Do-Check-Act (PDCA) procedure for

experimentation, a scientific method is followed. Through the application of the PDCA procedure, learning along the way is promoted.

2.1.4 Comments

Lean focuses on the whole value stream, in order to create flow through the value adding processes (Liker 2003). However, the analysis method suggested for the complete value stream is VSM. While such a method will help the user to understand more about the flow of products and information, and, to some extent, identify waste, it has the major drawback of omitting variability from the analysis, unless it is connected to simulation.

The Kata methodology might be useful for the improvements of current processes, and could be quite simple to apply, but it does not include methods that can explore the opportunities, make predictions, and gain knowledge about the way in advance. There would be an opportunity to create a map of the so-called gray zone, by applying state of the art methods, such as SBO, and making use of a truly scientific approach, as illustrated in Figure 2.4.

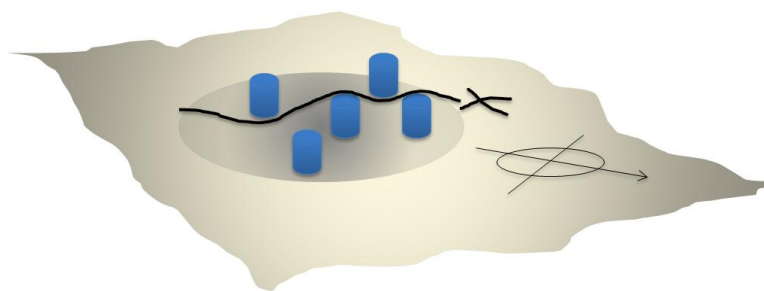


Figure 2.4. A map of the gray zone opposed to the Kata approach.

Exploring step by step and omitting the opportunities to explore scenarios, concepts, and obstacles in advance is reactive, instead of proactive, and a severe drawback in the Kata concept.

2.2 Six Sigma

Six Sigma is a statistical approach for the improvement of systems, and the development of products and services, related to key output variables and the reduction of customer defined effects rates (Linderman et al., 2003). It originates in methods for problem solving and measurements, developed within Motorola in the early 1980s. A spin-off from their work is the consulting and training company “Six Sigma Academy” (SSA). Through SSA, the Six Sigma methods are provided to others through consulting, instructions, and “black-belt certifications (Allen 2006). The Six Sigma training has quickly become very popular due to its linking of statistical techniques and measurement of outcomes in monetary or physical terms (Montgomery, 2001 and Hahn et al., 1999).

Improvement projects following the Six Sigma approach can be divided into five phases (Harry and Schroeder, 1999);

1. Define
2. Measure
3. Analyse
4. Improve
5. Control

The most common methodology used within Design for Six Sigma projects follows a similar set of phases (Cronemyr, 2007);

1. Define
2. Measure
3. Analyse
4. Design
5. Verify/Validate

Allen (2006) has abbreviated the various problem-solving methods connected to Six Sigma into a list, illustrating the breadth and the purpose of the methods. He then sorts

the methods according to their role and association to the phases in improvement projects, as shown in Table 2.1.

One of the major threats to production effectiveness is variation, according to Ignizio (2009), and Six Sigma can be used to reduce variation (Nave, 2002).

Some of the methods, within Six Sigma, considered to have a somewhat closer relation to SBO, are further discussed below.

Table 2.1. Six Sigma Methods associated to improvement project phases (Allen, 2006).

Method	Phases
Acceptance Sampling	Define, Measure, Control
Benchmarking	Define, Measure, Analyse
Control Planning	Control, Verify
DoE	Analyse, Design, Improve
Mailure Mode & Effects Analysis (FMEA)	Analyse, Control, Verify
Formal Optimisation	Improve, Design
Gauge R6R	Measure, Control
Process Mapping	Define, Analyse
Quality Function Deployment (QFD)	Measure, Analyse, Improve
Regression	Define, Analyse, Design, Improve
SPC Charting	Measure, Control

2.2.1 Design of Experiments

DoE is an essential ingredient in the Six Sigma toolbox. It is a statistical technique, introduced by Sir R.A. Fisher in England, in the early 1920s (Roy, 2001), which makes it possible to analyse the effect of more than one factor at a time. The process studied can be illustrated as a system with input, factors, uncontrollable factors (noise factors), and output, as in Figure 2.5.

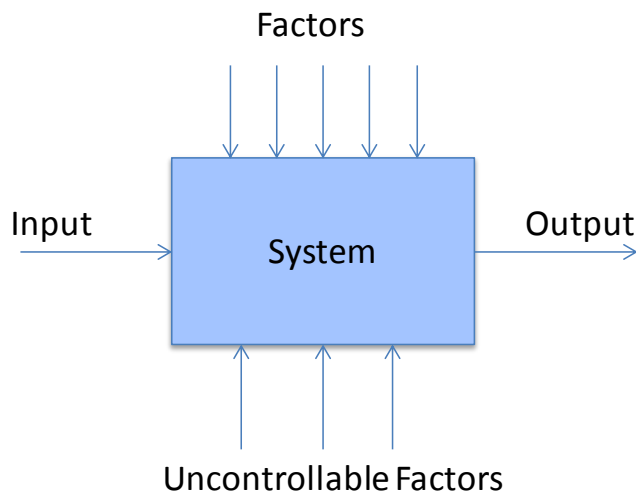


Fig 2.5. A process as defined when applying DoE.

This method has a structured approach for mapping, or collecting, response data from the variation of key input variables, through experimental tests. DoE is sometimes called the most powerful Six Sigma tool (Allen 2006). It can be used to explore a system, or a model, and search for high performing solutions and interaction among factors. One of the advantages of this method is that the response to parameter changes from a real-world system can be mapped. Another use is to explore opportunities with parameter settings, when connected to a simulation model. It is, however, a complicated tool requiring specialist knowledge to analyse the results and prepare information for decision-making. As such, the method has not been used much in production processes, since its academic development has made it less appealing to practitioners in industry (Roy, 2001). Another drawback is that DoE does not have the true ability to search for optimal or near optimal solutions.

2.2.2 Process mapping

The process mapping method is used to create flow diagrams of systems, clarify possible relationships between subsystems, and identify inputs and outputs. This type of mapping can be used as input to setup DES models, which plays a similar role to

process mapping (Allen 2006). A method closely related to process mapping, or actually another type of process mapping, is VSM, according to the definition of a value stream (Womack and Jones (1999), for the purpose of eliminating all unnecessary processing steps. The necessary steps, referred to as value added operations, are identified and all other activities are considered to be waste. This is not done in an ordinary process map. Another difference between process mapping and VSM is that a future state map is included in the VSM procedures.

2.2.3 Optimisation related to six sigma

Within Six Sigma optimisation approaches, various degrees of formality may be applied. When a low degree of information is available and a high degree of subjectivity is preferred, the optimisation procedures and the decision-making style are referred to as informal. High formality decision situations imply that a high level of emphasis is placed on data, and that a substantial amount of data is available for analysis, maybe combined with a large number of potential options, sometimes requiring computer assisted decision-making (Allen 2006). Formal optimisation within Six Sigma is often performed using mathematical approaches with models from DoE and regression analysis. Heuristic search methods and GA can be used within the Six Sigma approach, in order to explore data and models. However, these kinds of methods are not a predefined part of the common methodology.

According to Liker (2003), Six Sigma and Lean are sometimes considered to be two toolkits. Different groups in a company tend to go into combat about whose tool is the superior one, leading to a self-defeating improvement program. There is too much focus on tools and too little on philosophy and mindset. From this point of view, the training of Six Sigma and Lean experts tends to reinforce the tool orientation, instead of building a long-term way of thinking. Liker and Meier (2005) criticise several aspects of Six Sigma, as summarised below;

- The intense focus on data and analysis can be distracting and divert the focus away from the real purpose of the project.
- The promotion of analysis experts might lead to more analysis skills than knowledge about the process that needs to be improved.
- The experts can do too much on their own, reducing employee involvement.
- Results lacking ownership might lead to changes that do not last.
- Six Sigma lacks a real philosophy, besides finding, measuring and eliminating variation in order to save money.

According to Ha (2005), Six Sigma tools cannot effectively be used without a thorough understanding of statistics and the assumptions made behind each tool. One example is when data is assumed to be normally distributed, with 99.73 percent of the data within three standard deviations, and the actual distribution might not even be close to normal. The conclusion is that there is a major risk that wrong decisions will be made, due to incorrect analysis of data and misinterpretation of results.

Six Sigma is a powerful approach for the improvement of various systems and it can also be seen as a mindset with regard to the actual statistical meaning of Six Sigma that is formulated into trying to reduce the number of defective products from a process down to 3.4 parts per million (ppm). The focus is on improving a specific process, essentially value adding activities. Even when taking into account that the Six Sigma approach sometimes might stretch into the use of optimisation techniques, it is not a true optimisation method, especially when MOO and SBI alternatives are considered. The focus is more on finding robust solutions to improve quality towards the 3.4 ppm objective. DoE can be used to map interactions between inputs and outputs in existing systems and might be used on conceptual systems when connected to simulation models. Controlling a simulation model with the help of DoE can enable partial exploration of the objective space. Finding optimal, or near optimal solutions, to a problem, or finding a multi-objective Pareto frontier, is not within the normal scope, or

the intended use, of the method. Nor is further objective space exploration and knowledge extraction included in the Six Sigma approach.

2.3 Theory of constraints

A production system is defined as a series of interdependent processes analogous to a chain, and the interdependent links all work together towards a common goal. The weakest link is the constraint. In order to improve the production system's throughput, operational expense, or inventory, the ToC suggests improving the constraint of the system (Goldratt, 1984).

The improvement procedure according to ToC comprises five steps:

1. Identify the constraint.
2. Exploit the constraint.
3. Subordinate other processes to the constraint
4. Elevate the constraint
5. Repeat the cycle.

The first step is to identify the constraint that is degrading the performance of the system. The second step suggests improvement of the constraint, or to support the constraint, in order to maximise capacity without costly changes or upgrades. The third step includes pacing the processes, especially ahead of the constraint, by reducing their speed. If more output is required from the system, the fourth step involves major changes to the constraint, including substantial expense, if necessary. When the first constraint is removed, another process will become the constraint and the improvement cycle is repeated.

The first step requires the constraint to be identified and this might be the weak link of the method, since a classic indicator would be the amount of work in queue ahead of a process step. Another drawback is the inability to foresee the next improvement step until the former has been implemented. The application of ToC in combination with a

method for constraints detection could, at least to some extent, overcome these weaknesses.

2.4 Factory Physics

Factory Physics is defined by Wallace and Spearman (2008) as “a systematic description of the underlying behaviour of manufacturing systems”. They briefly summarise the opportunities that are opened by understanding these behaviours and being able to work with the natural tendencies of manufacturing systems as follows:

- Identify opportunities for improving existing systems
- Design effective new systems
- Make the trade-offs needed to coordinate policies from disparate areas.

These statements might be accurate to a large extent, but could also be challenged by other methods claiming to address such issues as well.

Factory Physics is based on a set of principles, defined through mathematical expressions and equations, such as Little’s Law, worst-case performance and practical worst-case performance. Other principles are formulated as statements, such as “Increasing variability always degrades the performance of a production system”.

The essential aspects of systems analysis are as follows:

1. A systems view
2. Mean-ends analysis
3. Creative alternative generation
4. Modelling and optimisation
5. Iteration

The first step emphasises the importance of a broad, holistic view of a problem, relating to its context in a system. The second step focuses on specifying the objective, or

objectives, to be used when evaluating alternatives according to the third step. In this step, a broad perspective, with a system approach, is held when seeking alternative solutions. The fourth step aims at quantifying the alternatives and comparing them to the objectives. Various methods for modelling and optimisation can be used, depending on the complexity of the system and the potential impact of the resulting decision. The fifth step implies that objectives, alternatives, modelling, and optimisation are repeated in a learning process, especially when analysing complex systems.

Ignizio (2009) uses three fundamental equations to model factories, in order to investigate the impact of variability and throughput capacity on factory performance. He concludes that these equations are “mostly of academic interest and of limited practical value since the prediction of performance of more complex factories are, at present, best achieved via DES models”.

2.5 Conclusions

Various methods that address different problems and challenges are available for production systems development and improvement. Lean focuses on the whole value stream, in order to create flow through the value adding processes (Liker 2003). The idea of VSM is to reduce waste by creating a connected value stream and improving the flow through the plant. TPM and loss models are striving to use time and resources for value adding activities only. The focus of Six Sigma is on finding robust solutions to improve quality. The ToC suggests improving the constraint of the system, in order to improve the production system’s throughput, operational expense, or inventory, (Goldratt, 1984). Factory Physics is defined as “a systematic description of the underlying behaviour of manufacturing systems” (Wallace and Spearman, 2008).

Some that advocate a specific philosophy, method, or tool may criticise other doctrines, but are themselves sometimes challenged by others. According to Ignizio (2009), the focus should be on reducing complexity and variability, in order to achieve significant and sustainable factory performance. While Lean manufacturing, Six Sigma, and TPM

offer the potential to support such efforts, they should not be applied in isolation. It is essential to apply manufacturing science and simultaneously consider the impact of culture and politics. Furthermore, according to Ignizio (2009), improvement through the reduction of complexity and variability “can only be accomplished by expertise in the science of manufacturing with real leadership at the top”.

Based on the literature review, some vital drawbacks of, or rather deficiencies not addressed by, current methodologies for production systems development and improvement have been identified. These issues might lead to inadequate production solutions, low effectiveness, and high costs, resulting in poor competitiveness. Considering the harsh market situation, there is an urgent need to address this problem in order to regain profitability in many enterprises. The most important findings can be concluded as follows:

- Lean does not consider the effect of variability on the overall line performance enough and its current production flow analysis methods do not take variability into account, unless they are connected to simulation.
- Decision-making is often based on tools, or methods, that cannot reveal enough information or knowledge about the problem.
- Exploring step by step and omitting the opportunities to explore scenarios, concepts, and obstacles in advance is reactive instead of proactive and a severe drawback of the Kata concept.
- Finding optimal, or near optimal, solutions to problems is sometimes considered, but limited to simple cases and theoretical problems. It seems that true optimisations of complete production lines are rarely considered or applied.
- Several methods and theories require that the constraint, or the bottleneck, of the system is known. Strategies to find the real constraint or the real bottleneck are not incorporated into such approaches. There are methods with the ability to identify a bottleneck as a production step that includes a constraining factor for the system, as long as the system is fairly simple. Finding the true bottleneck,

the cause of it, and simultaneously proposing the type of countermeasure required for improvement, through a simple analysis, is not possible using current methods.

- The methods available for bottleneck detection and production flow analysis do not enable the simultaneous evaluation of cost impacts, or ranking in order of importance, from a single analysis.

Chapter 3.

A Methodology for Manufacturing Management using MOO

In this Chapter, a framework that supports decision-making for production systems development and improvement is presented as a hypothesis to address the problems identified in Chapter 2. First, the proposed methodology is introduced, and then a literature review on simulation-based MOO, the concept of “innovization”, and the PrOACT decision-making method serve as a foundation for the design of the framework. Finally, the method and the framework are presented in more detail.

3.1 Methodology introduction

Industry often relies on lean methods to solve production issues (Pehrsson, 2009) and although lean is a necessary approach it is not sufficient for the analysis of production system issues (Standridge and Marvel, 2006). Some of the drawbacks with current methods, identified in Chapter 2, could be addressed by introducing a new framework for production systems design and improvement using simulation-based MOO and post optimality analysis for knowledge extraction. During the development of production systems, there is always an on-going search for better methods and solutions, ideally innovations, in order to enhance performance and gain competitive advantages. The production systems are developed and optimised towards one or more objectives, using various strategies, methods, and tools. The framework is believed to help a decision maker by transforming production system data into knowledge about the system. Such a framework can be used as an entirely new strategy for improving production system performance or to complement current methods and philosophies, in order to enhance

their strengths. The integration of SBO and MOO, or SMO, has opened the opportunity to find the optimal or near optimal solutions with regard to several objectives within certain constraints. So far, SMO, applied on production systems, has been used to target traditional production system objectives, such as throughput, WIP, and lead time. In combination with post-optimality analysis, the concept of SMO has the potential to create a foundation for decision support introduced by Deb with the name “Innovization” (Deb and Srinivasan, 2006; Ng et al., 2009). The concept of innovization with knowledge extraction from optimised data together with a procedure for problem definition, modelling, analysis, and decision-making constitute the essential ingredients for the design of the proposed method.

3.2 Literature review

In order to build a foundation of the proposed framework, simulation-based MOO, the concept of innovization, and the PrOACT method for decision-making have been explored.

3.2.1 Simulation-based multi-objective optimisation

Simulation and especially DES is used for the evaluation of production systems performance. Complicated production lines and systems can be evaluated through the modelling of the objects and events occurring in a real system, taking variation and stochastic behaviour into consideration. Simulation is actually the only general purpose and generally applicable modelling tool for truly complex systems (Fu et al., 2000). The downside is often a long lead-time for modelling and experimentation. This is, however, something that in many cases can be overcome by the application of modelling tools for simplified conceptual modelling (Ng et al., 2007). The simulation method by itself provides the evaluation of a given scenario, but does not optimise the system, and since simulation is not an optimisation tool, a step that combines simulation and optimisation is needed (AlDurgham and Barghash, 2008). With the addition of optimisation techniques, input parameters for a simulation model can be altered and controlled by an

algorithm, in the search for solutions that best satisfy an objective. MOO provides the opportunity to search for trade-offs between several conflicting objectives (Deb, 2001). Algorithms for MOO can be classified into exact and approximate (heuristic) algorithms that can be further divided into specific heuristic, designed to solve a specific problem, and metaheuristic which is more generally applicable and problem independent (Talbi, 2009). Recent development in the optimisation field is towards many-objective optimisation, since most existing evolutionary multi-objective optimisation (EMO) algorithms have difficulties handling more than three objectives (Sinha et al., 2013).

3.2.2 Innovization

The “Innovization” concept introduced by Deb and Srinivasan (2009) can be described as extracting innovative design principles through post-optimality analysis of data from multi-objective optimisation or, more simply, innovation through optimisation. Innovation as defined by the Merriam-Webster Encyclopaedia is “the introduction of something new” or “a new idea, method or device: novelty”.

In some optimisation tasks, especially during the design of products, GAs are used. Algorithms of this kind can, to some extent, be considered as a model of innovation (Goldberg 2002). Based on evolving populations of solutions, a GA can have a variety of operators generating new solutions. Some common ones are selection, recombination, and mutation. Selection will promote the survival of the fittest solutions, while recombination can create a potentially better offspring and mutation enables the ability to find solutions in the neighbourhood of a solution. According to Goldberg, the combination of selection and mutation leads to a hill-climbing mechanism that will evolve towards better solutions in the neighbourhood of a solution, much like a kaizen process (Liker and Meier, 2005) used for continuous improvement. Selection and recombination can be considered an innovation process by cross-fertilisation of good solutions which might create better solutions than the original ones in a previous generation. Hence, the opportunities for innovation to occur are built into the concept of

a GA. One conclusion from this is that there is a probability that innovative solutions are present in the results from an optimisation performed with GA. In the case of single objective problems, the optimisation process can result in an innovative solution (Goldberg 2002). While such solutions can be found in the data resulting from optimisation and applied to solve a problem, there might be little knowledge regarding what distinguishes a good innovative solution from a worse solution, parameter-wise. With regard to data from MOO, individual parameter settings for a specific solution can be found by connecting the objective space to the decision space without understanding essential principles and the knowledge required to reach a certain region on the Pareto frontier, illustrated in Figure 3.1.

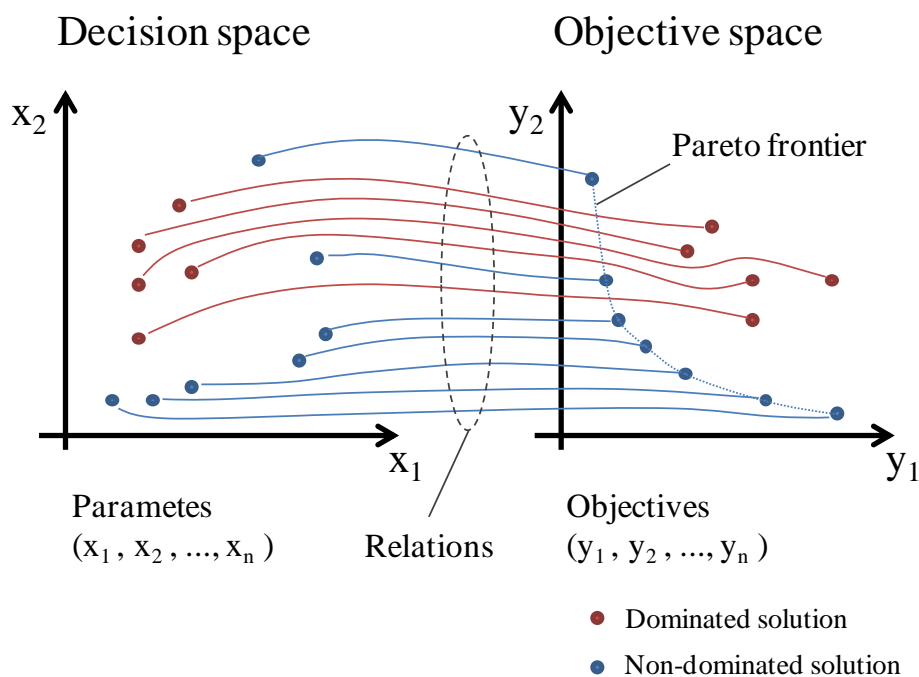


Figure 3.1. Decision space and objective space.

Solutions on the Pareto frontier are the so-called non-dominated solutions. For a non-dominated solution there is no better solution in the objective space, with regard to one of the objectives, without being worse in at least one other objective. A vector is

efficient (non-dominated) if not dominated by any other feasible vector (Miettinen, 1999).

The concept of “Innovization” as proposed by Deb and Srinivasan (2009) suggests combining MOO with various post-optimality analysis techniques, in order to extract and decipher knowledge from optimal solutions. The idea is to find new and innovative design principles, by revealing deeper knowledge about a problem, rather than just finding a set of Pareto-optimal solutions. Deb thereby extends Goldberg’s argument from achieving an innovative design for a single-objective scenario to a systematic approach that builds on MOO and the subsequent analysis of optimal solutions. Insights about the problem and design principles common among optimal trade-off solutions are sought, rather than a single optimal and perhaps innovative solution just being found. When minimising or maximising towards one objective, usually one optimal solution is the target, according to Deb. This does not provide any deeper understanding other than just the setup to achieve the optimal solution. With two or more conflicting goals, it is possible to study a set of Pareto-optimal trade-off solutions and analyse them for interesting commonality principles. Early application based on the innovization concept has been related to engineering design issues. The concept of innovization is in some ways related to computer-aided innovation, since it uses optimisation techniques as a means in the innovation search. Computer-aided innovation explores the design space and then adds a creative step to redefine the design space, objectives, and constraints (Cugini et al., 2009). Leon (2009) maintains that the optimisation techniques have evolved because they are efficient in finding a solution, if it exists within the search space, and theorises that it is possible to use optimisation techniques to include properties other than just parameters, in order to find solutions to problems that cannot be solved with conventional methods. This new optimisation method could be referred to as Computer-aided Inventive design. The innovization process is evolving into an iterative process, involving the decision maker in several steps, with the opportunity to redefine objectives, parameters, constraints, and the design space (Deb et al., 2010; Ng et al., 2012). The application of knowledge extraction techniques in the iterative process

supports informed decisions and the reformulation of the problem, if required. Recently, automated innovization was proposed (Bandaru and Deb, 2010) to address some of the drawbacks with human cognitive limitations to perceive interactions in higher dimensions, together with reducing time consumption for manual analysis tasks and to handle data transformations for the identification of non-linear correlations. Additionally, the risk of human errors is reduced through an automated process. Bandaru et al., (2011), Bandaru and Deb (2013) also introduce the new concept of higher- and lower-level innovization. The higher-level innovization targets the extraction of common design principles from a number of trade-off datasets, while the lower-level innovization can be applied to a partial set of trade-off data, in order to obtain design principles exclusive to the selected data.

An emerging application field for innovization is within production systems engineering. SBI for production systems, suggested by Ng et al., (2009), incorporates three major steps:

1. A solution set is collected through SMO.
2. Hidden knowledge is extracted.
3. A knowledge base for future use is developed.

The data set containing multiple trade-off optimal solutions is generated by performing an EMO on a DES model of the production system. The extraction of hidden data can be performed by applying, e.g., various data mining techniques on the data set (Dudas et al., 2011). Relevant knowledge from the study is stored, in order to be used as input for future designs and decisions. According to Dudas et al., the combination of MOO solutions and data mining is a fairly unexplored area and they only found two relevant articles – (Chiba et al., 2006; Jeong et al., 2005), both regarding aerodynamic design optimisation problems. The application of innovization within manufacturing and production systems engineering is a field currently being explored and a few publications on the subject have emerged (Ng et al., 2009; Dudas et al., 2011) in parallel to the work on this thesis.

3.2.3 Decision-making and the PrOACT method.

Some decisions are fairly obvious to make and the ability to make choices is a fundamental life skill, but easy decisions are exceptions. Most important decisions are tough and complex and, in order to support decision makers to make better choices, Hammond et al., (1999) propose the PrOACT decision-making method, in their book *Smart Choices*. Resolving a decision situation that has several objectives and alternatives tends to be a complex task. The authors of *Smart Choices* have distilled and summarised the decision-making research, claiming that the process of making decisions should be turned into a technique used to make smart choices. A proactive approach to decision-making and decision situations is to prefer, as the acronym PrOACT indicates. It is better to make a decision than to be forced into one or to wait for a decision to be made for you. Hammond et al., (1999) have identified eight elements of decision-making and integrated them into their method. The essence is to focus on key issues, divide and conquer, in order to resolve a complex decision situation. The eight elements are briefly summarised below:

1. **Problem.** What is the right decision problem? The decision problems must be stated clearly, with regard to complexity, as well as avoid prejudices and superfluous assumptions.
2. **Objectives.** The objectives will give direction to the decision-making and should get you where you want to go. The objectives must be carefully thought through and be relevant, in order to be achieved.
3. **Alternatives.** The alternatives actually create the decision situation. Without alternatives, there would be no decision to make. It is important to evaluate if all relevant alternatives have been taken into consideration. A creative process could generate more alternatives to choose from.
4. **Consequences.** The alternatives that best meet all the objectives can be identified, if the consequences of the alternative decisions are assessed.

5. Trade-offs. Objects are frequently in conflict with one another and the decision might include balancing and sacrificing something in order to gain another benefit.
6. Uncertainty. Choosing an alternative is more complicated due to uncertainty, considering the likelihood of different outcomes and assessing their impacts.
7. Risk Tolerance. A conscious awareness of the willingness to accept risk will make the decision process smoother, more effective, and enable the choice of a solution with the right risk.
8. Linked Decisions. Many important decisions are linked over time and the goals for tomorrow should influence the decisions today. It is of key importance to isolate and resolve near-term issues and sequence actions.

The PrOACT method can be related to and used for multi-criteria decision analysis (Mustajoki and Hämäläinen, 2007), optimisation problems and the subsequent decision-making. There are many similarities and connections between the process of MOO and the first five elements of the PrOACT method. First of all, an optimisation problem must be defined. In the case of production system development, it might concern selecting between equipment suppliers, alternative production methods, layout considerations, buffering setup, and dispatching strategies. In order to make a model and run an optimisation, the problem must be carefully described. Then the right objectives must be selected. When applying MOO, several conflicting objectives can be considered simultaneously. Such objectives might concern different units that are possibly not directly comparable. The alternatives are defined by input parameters and constraints forming the decision space. The consequences are investigated through the optimisation process and then illustrated through the objective space, the results from the optimisation. When handling conflicting objectives during optimisation, the concept of finding non-dominated solutions is applied. An analogy is to be found when applying the even-swap method for evaluating alternatives, by removing dominated solutions from the final decision-making in a trade-off situation (Hammond et al., 2001). Hence, the first five elements of the PrOACT method correspond very well with the process of

MOO. The remaining three elements, uncertainty, risk tolerance, and linked decisions, must be considered in both cases and can be supported by extraction of knowledge about the system, through post-optimality analysis. The extracted knowledge might reveal information related to these elements, such as parameter settings or combinations of parameter settings leading to certain system behaviours or results. Replications in the simulation procedures can provide some information that is essential for the evaluation of risk tolerance. Furthermore, the evaluation of many combinations of options can help the decision-maker find preferred decisions.

In addition to decision-making and the PrOACT method, Hammond et al., (1998) present a number of pitfalls to be aware of in decision situations. There is a risk in every step of decision-making for misperceptions, biases, and other psychological miscues that could influence choices. “Highly complex and important decisions are the most prone to distortion because they tend to involve the most assumptions, the most estimates and the most inputs from the most people” (Hammond et al., 1998). Hence, methods that reduce the number of assumptions and provide better estimates with fewer inputs from fewer people could potentially enhance decision-making.

3.3 Developed for multi-objective optimisation

The proposed framework supporting decision-making for production systems development and improvement has been developed to be used with MOO as an enabler to find trade-off solutions for conflicting objectives. The combination and re-combination through the cross-fertilisation mechanisms in such a method will also include a probability that innovative design solutions can be found (Goldberg 2002). The proposed method is meant to help a decision maker base the decisions more on knowledge and facts, as shown in Figure 3.2, than on just bare data, as illustrated in Chapter 1 (Figure 1.2).

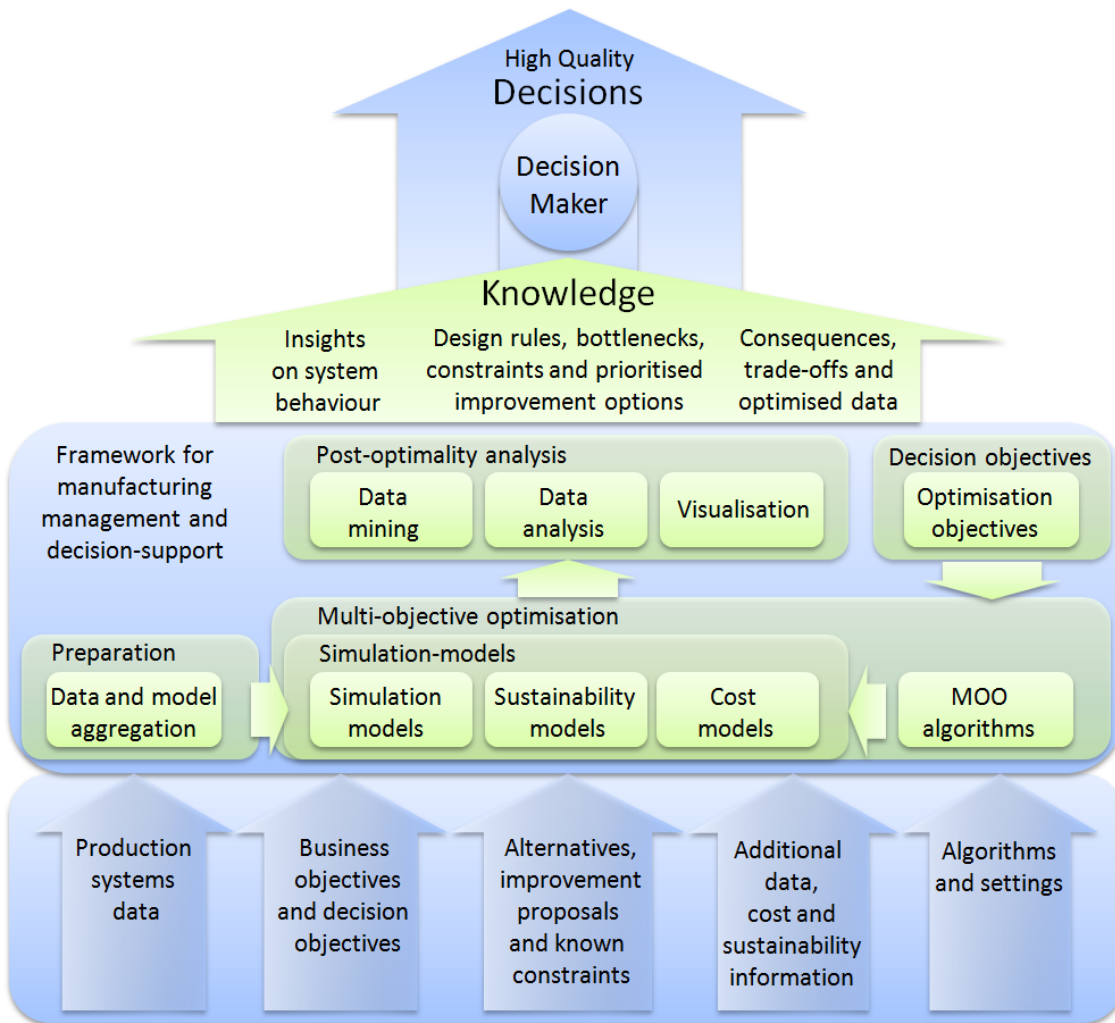


Figure 3.2. Framework for enabling decision-making based on knowledge rather than raw data.

The ability to include variability as an essential factor in production system analysis is a prerequisite, in order to address some of the drawbacks with current industrial flow analysis and process analysis methods. DES is an approach including variability and at the same time offering the possibility to evaluate scenario and concepts proactively. The concept of innovization includes opportunities for post-optimality analysis and knowledge extraction through visualisation techniques and data mining. By paying attention to the elements of the ProACT method in combination with a careful selection of tools for simulation, optimisation, and data analysis, a solid foundation for decision-

making can be established and compiled into a framework and procedure for manufacturing management decision support to be used within the development and improvement of production systems.

3.4 Procedure in detail

The proposed framework can be illustrated through a process containing the essential steps to be conducted when using it as a method for the creation of decision-support, as shown in Figure 3.3. The modelling and data required will vary depending on the development strategy for the system and the strategy should be known before applying the improvement procedures.

3.4.1 Problem definition

Before the proposed method can be applied, the decision-making problem and consequently the optimisation problem must be defined. It can be the design of a new system or the improvement of an existing system, based on the development strategy. The decision might concern the selection of production methods, process parameter settings, choice of equipment and suppliers, evaluation of flow and layout alternatives or it might be a decision concerning where and what to improve, given that the current performance of the system is inadequate. When dealing with production systems, it is most certainly relevant to use some kind of DES model, since predicting production systems performance is best achieved via DES (Ignizio 2009). The problem must be thoroughly examined and the data requirements to model the system analysed must be established. In the case of conceptual analysis or the design of a new system, the data available might be less detailed and the modelling aggregation must be adapted accordingly. For the evaluation of existing systems, the opportunities with more data available must be considered. The vast majority of models are simplifications or abstractions of reality (Sanchez, 2006) and the model abstraction should be adapted to the decision situation. The main reasons for model simplifications are to reduce effort,

time, and the cost of modelling (Chwif et al., 2000 and Madam et al., 2005) as well as decrease the execution time of the simulation (Johnson et al., 2005).

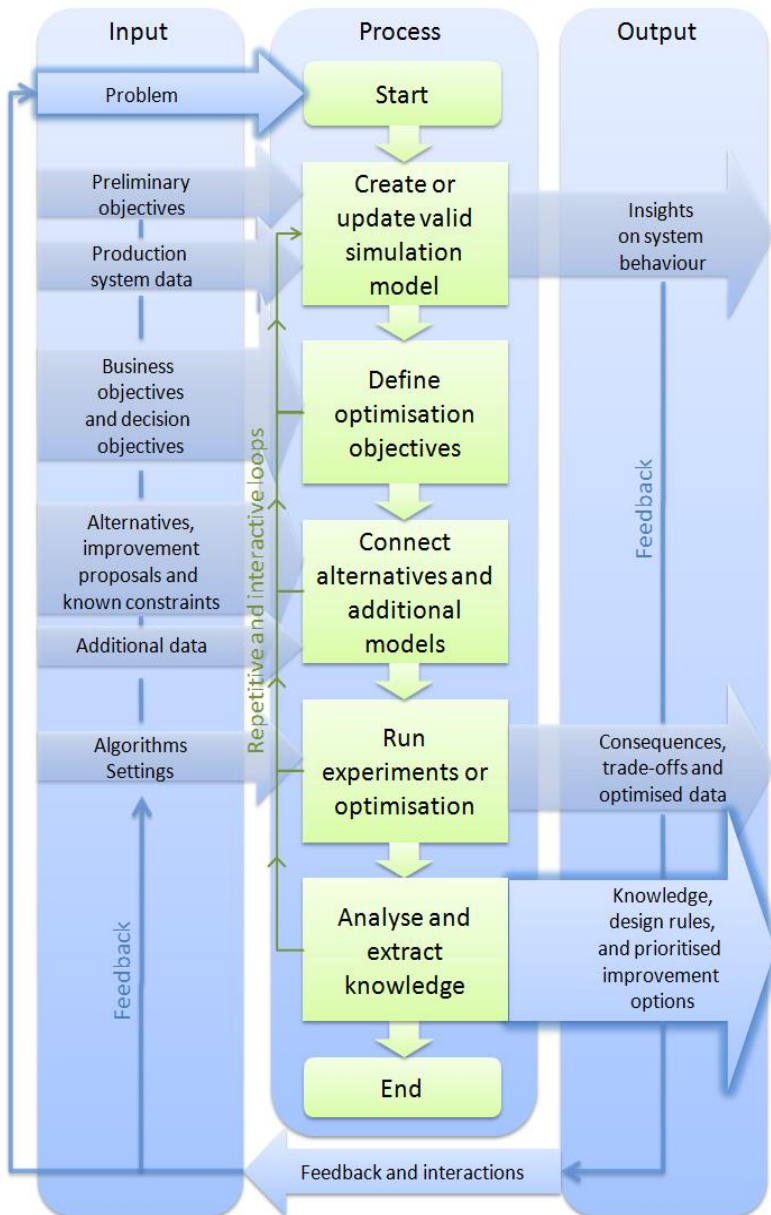


Figure 3.3. Generic process for the creation of decision support using the framework.

The nature of the evaluation to be performed is also an essential prerequisite for determining the suitable level of models and data abstraction. The various types of

models required to evaluate the system with regard to the objective in question must also be established. Some problems might require models for the evaluation of monetary aspects or resource consumption. Aggregated simulation modelling can be applied for conceptual decision-making (Urenda Moris et al., 2008) with tools allowing a high abstraction level, such as Facts Analyser (Ng et al., 2007). More detailed evaluations will require models with more details, a lower abstraction level, and tools accordingly.

The thorough calculation of one or several initial scenarios can be of great benefit, since they can be modified by adding or subtracting differences when evaluating alternative solutions. A collection of benchmarking data for various process options can be very valuable for the evaluation of options within a short lead time for decisions.

3.4.2 Simulation model

A prerequisite for the optimisations of a production system is a valid simulation model taking into account the output variables needed to evaluate the objectives and the input data and input parameters required. Another important input is the preliminary optimisation objectives. The framework is designed with the DES production systems modelling technique in mind and despite the fact that other modelling techniques might work, DES is recommended. The aggregation level of the model and the data should be aligned with the expected accuracy. A model built at a relatively high aggregation level with high quality input data might be more useful for decision-making than a model attempting to include all real-world details with less accurate input data. For fast decision-making with regard to conceptual choices in early development phases, less accurate models and data can be used, while decision-making with regard to more in-depth properties in existing production systems might require more detailed models and more accurate data. During the process of modelling, collection and examination of data, constraints identification and the determination of optimisation objectives, knowledge about the systems prerequisites and behaviour will increase together with a

better understanding of the decision situation. With separate sub-models in place, it is time to reflect on the integration and performance of the complete system model. Sometimes the model needs to be updated to take advantage of the knowledge gained in other process steps.

3.4.3 Data

The usefulness of the framework, the quality of the optimisation process and, finally, the decision-making all depend on the data available. The creation of a valid DES model usually requires data that at least includes station cycle times, availability, mean down time (MDT), buffer capacities and transport time, besides information about the flow and various control and dispatching rules, in order to be able to evaluate the most basic production system objectives. If some type of aggregated objectives are to be evaluated, e.g., running cost or investments, more data is required accordingly. Often, when it comes to decision-making in the conceptual phases of production systems, the lead time from an idea to a decision is very short and many times a multitude of alternatives are considered. In order to facilitate decision-making under those circumstances, much of the data must be prepared in advance. It is imperative to have data from existing operations and estimations on various scenarios.

3.4.4 Defining the optimisation objectives

The next step is to identify objectives that will drive the optimisation towards supporting the decision situation. For a production system, such objectives might include one or several of the following examples: maximise throughput, minimise the system's cycle time (leadtime), as well as WIP, the required number of buffers, the running cost, energy consumption, amount of investment, the number of palletes, or minimise the amount of resources required. These are just a few examples that provide some background on relevant objectives. Some of these objectives require additional models besides DES or in combination with DES.

3.4.5 Alternatives: Input parameters, parameter constraints, and improvement proposals

In order to optimise the system towards the objectives, it is essential to select the right input parameters and their ranges. The parameters often have boundaries limiting them to a certain range. Sometimes the exploration of knowledge about the system can be enhanced by allowing wider parameter ranges. The most innovative solutions from a system perspective might require that several, or maybe just one, of the parameters are outside the range considered normal. If there is much to benefit from such a configuration, it might be possible to change some conditions in order to enable a certain setting. Hence, it is sometimes important to think a little outside the box when selecting parameters and their ranges. Parameter ranges that are too wide should however be avoided, since increasing the complexity of the optimisation problem will require more computational resources. One way of reducing such complexity is to find out the most important limiting factors (constraints or bottlenecks) of the production system studied. By focusing on alternative countermeasures to the most prominent constraints, there is a potential to gain substantial improvements. Again there is a connection to the PrOACT method which states that alternatives actually create the decision situation. Without alternatives there is in fact no decision to make. In this phase, it is vital to remember that the options, parameters or alternatives included in the optimisation problem will set the boundaries for how well the objectives can be met. If the right parameters and ranges are present, there could be some probability that innovative solutions can occur (Goldberg 2002). Often, parameters used as input can double as an objective or be included in the calculation of an objective. For example, when optimising the number of palletes in a system, which is a minimisation problem, it concerns the minimum number of pallets to be released into the system, presumably while throughput is maximised. The parameter is used as input and objective at the same time. An example of when input parameters are used to calculate an objective is during a lean buffer optimisation when each buffer's capacity is input and the total sum

of all the buffers' capacity is an objective for minimisation with simultaneous maximisation of throughput. Other types of selections or choices may be used as input parameters. These are often selections between various methods, types of equipment, processing options, control options, dispatching rules or flow alternatives. Another example is various improvement proposals with different local effect and various costs attached. Such parameters can be converted into discrete numbers representing each option. One of the advantages of using Simulation-based MOO with GA is the opportunity to mix continuous and discrete variables. Optimisation of other objectives than traditional production system parameters will require specific models to be connected to the DES model, in order to generate output that enable the evaluation of those objectives. Some models for cost and sustainability evaluations, considered to be essential for the creation of useful decision-support in manufacturing management situations, are included in the framework. When these models are connected to a DES model, a production system can be optimised, with respect to running cost and investments, in combination with various sustainability objectives. Cost modelling and sustainability modelling techniques are proposed and tested in Chapters 4 and 5. The industrial application and validation of the framework with cost modelling techniques can be found in Chapter 7.

3.4.6 Optimisation

When there is a validated model with adequate data, parameter ranges, and optimisation objectives, it is time to set up the optimisation. Besides selecting an adequate optimisation algorithm with correct settings, the setup of the optimisation mainly concerns connecting the algorithms to the models through input parameters, output parameters, and objectives. The use of multi-purpose metaheuristic optimisation algorithms is recommended, in order for the framework to be generally applicable on a wide variety of problems. The parameter ranges that the algorithm is allowed to control must be coupled with the correct parameters in the model. In addition, the output and input parameters required for the evaluation with regard to the objectives must be

monitored. When a stochastic model, such as a DES model, is involved in the analysis, the use of replications is recommended, in order to handle noise due to stochastic variation and to support accuracy expected for decision-making. In some situations, dynamic re-sampling techniques (Syberfeldt et al., 2009) could be used to reduce the total number of replications in a simulation run. Often, the simulation horizon, if selected long enough, will reduce the need for many replications, since time will smooth out temporary effects of variation in the system. It is, however, vital to select a simulation horizon that reflects the decision situation. In a situation where the number of produced items per week is one of the essential objectives, the simulation horizon should presumably reflect that and be set to a week.

The optimisation procedure, when using GA, will involve a large number of simulations that form generations. These generations of simulations will be allowed to evolve towards optimal solutions on a Pareto frontier in an automated process. In some cases the procedure might start with some kind of random search, e.g., based on Latin hypercube sampling (LHS), roughly scanning and defining the objective space for the decision maker. Such a random search would also provide the opportunity to find information about parameter settings that should be avoided. Parameter settings or a combination of settings that are of essential interest to the decision-maker could end up in solutions far from the Pareto frontier. Sometimes an interactive process might be beneficial, in order to take advantage of a decision maker's preferred target of the optimisation. The reason for this may be to reduce the computing power requirements or to reduce lead time. After a rough exploration of the decision space, the decision maker's preference can be included in the optimisation, e.g., through the application of rules and constraints that restrict parameter ranges, or through reference point based algorithms that target the optimisation by promoting a certain direction. This technique can be applied in several subsequent steps. While some kind of data analysis might be required between these steps, more or less of the complete process may be iterated, so that sequential decisions can be made towards the final decision. It is often more practical to just run one optimisation, based on well-prepared models, data, parameters

and objectives, and follow it with a thorough post-optimality analysis for the creation of decision support. However, the learning process through iterative decision-making should not be underestimated.

3.4.7 Post-optimality analysis and visualisation

One of the main objectives of the proposed framework is to support decision-making based on knowledge rather than raw data and, by running an optimisation, even more data is actually created. While the direct results from optimisation could be used for decision-making, simply by trying to find and select good solutions in the resulting data, in most cases this is not a very practical procedure. The minimum analysis required would be to plot the data, in order to reveal information about the objective space as a means of selecting solutions. However, not much knowledge about ulterior parameter dependencies or design principles can be gained that way and more analysis would be of interest for the development and improvement of a system. It is really the further analysis of data from optimisations that can enable the creation of knowledge to support the decision maker. By linking the objective space back to the decision space, the relations between objectives and input parameters can be established. Some settings in the input parameters may result in objective space clusters that conceal recipes and design principles useful to the decision maker. A methodology and technique for revealing relationships in the data, such as data mining, would be required. "Data mining is an interdisciplinary field with the general goal of predicting outcomes and relationships in data" (Choudhary et al., 2008) and according to Weiss and Indurkha (1998) "data mining is the search for valuable information in large volumes of data. Weiss and Indurkha (1998) have divided data-mining problems into two general categories, "prediction" and "knowledge discovery". Knowledge discovery is said to complement predictive data mining and is closer to decision support than decision-making. When combined with optimisation procedures, the edges blur somewhat, since knowledge discovered from simulated and optimised data may contain predictions of performance for future systems instead of past experience with known answers. The

category of knowledge discovery problems is formed by “deviation detection, database segmentation, clustering, association rules, summarisation, visualisation, and text mining” (Weiss and Indurkha, 1998). According to Weiss and Indurkha, “visualisation techniques are of primary interest for discovering new knowledge” when data is not yet organised in some standard form with features and goals. Kopanakis and Theodoulidis conclude that “visual data mining techniques have proven to be of high value in exploratory data analysis”. Visual data mining techniques aim at an integration of visualisation and data mining, in order to enhance the effectiveness of the overall data mining process. Simson and Domndelinger (2009) also suggest visual techniques for the exploration of multi-dimensional data from optimisations. Some of the methods used to create decision support visualisation are: 4D-plots, colour coding, parallel coordinate (PC) plots and clustering by analysing step effects. In the end, it is all about revealing information and knowledge to the decision maker and clarifying the trade-offs available.

3.4.8 Identification of system constraints

A special application of the framework is to search for constraints in a production system. In some cases, the decision maker can be aided in setting up and perhaps simplifying the optimisation problem, if the system’s major constraints, related to the decision situation, are known. If there are, e.g., pronounced bottlenecks in the system or very costly processes, it might be wise to find such obvious obstacles before setting up the final optimisation. A common analysis of constraints is to perform a bottleneck analysis, if one of the objectives is throughput or dependent on throughput. By ranking constraining processes and process parameters, the optimisation problem can be narrowed down to essential parameters and more focused towards the objectives. Previously existing methods, such as shifting bottleneck detection technique, might be used, although due to limitations with current methods for bottleneck detection, a new approach, based on the SMO decision-support framework, is proposed in Chapter 6. The new method, referred to as Simulation-based CONstraints Removal, optimises

where improvement would be most beneficial and sorts out the constraints according to rank through frequency analysis.

3.4.9 Decision-making and manufacturing management

Decision-making is part of all steps in the process and involving the decision maker in the process of preparing decision support could be very valuable, since preferences can be added and it could facilitate learning and gaining insight during the process. With the right preparation of optimisation problems, it is possible to create decision support for a wide variety of manufacturing management issues, from the evaluation of strategies and the design of new systems to improvement prioritisation and the detection of constraints. The framework should be applicable at production line level, as well as supply chain level or process level. With a combination of objectives from various disciplines, such as production, engineering, maintenance, finance, and logistics, the method can enable the creation of decision support revealing interdisciplinary trade-off opportunities, relations, and knowledge of great value. The proposed method is believed to reduce the number of assumptions and provide better estimates. Thereby, it has the ability to create support for enhanced decision-making, by counteracting distortions in the decision situation.

3.5 Summary

A framework for decision support for manufacturing management as well as production systems development and improvement has been proposed as a hypothesis to address the weaknesses of current industrial methods, identified in Chapter 2. The idea is to elevate decision-making based on raw data to a level where, to a greater extent, it is based on knowledge about a system, available options and trade-off opportunities. The PrOACT decision-making method is used as reference, in order to ensure that the most important decision-making criteria are met by the proposed framework. DES techniques

take variation into account and can be used to evaluate concepts or future strategies. The incorporation of MOO is an enabler to find trade-off solutions for conflicting objectives and, together with post-optimality analysis and knowledge extraction from optimised data, such a framework has the potential to facilitate decision-making based on knowledge. With cost models, presented in Chapter 4, and models of sustainability, presented in Chapter 5, connected to the models of production systems, new optimisation objectives can be used to enhance the prerequisites for decision-making within manufacturing management, as well as production systems development and improvement. A special application of the framework is a new bottleneck (constraints) detection technique, proposed in Chapter 6.

Chapter 4.

Cost Modelling including testing

The purpose of this chapter is to propose and test a cost modelling method for integration in the framework for manufacturing management and decision-support, using SMO, proposed in Chapter 3. An introduction that includes some background and a literature review of cost modelling is followed by theories of industrial cost modelling. Then a cost modelling method is proposed and tested through integration with the decision-support framework. Finally, the findings are presented and summarised.

4.1 Introduction to cost modelling

According to Gustavson (2010), the general goal of production systems design is to find a resource that produces the minimum cost on a task-by-task basis. That way, the system will have a very low cost when all tasks have been assigned. Gustavson also states that there is no current method to prove that the results are optimum. The time available and the allocation of time are considered fundamental pieces of information required for system design. Some of the other factors mentioned are the fixed cost of a station, the variable cost for a task, and using activity based costing (ABC) and quality rating, numerically equivalent to the unity cost of a station. Achieving the best possible production systems using current methods is said to usually be, and will continue to be, a difficult and time-consuming trial-and-error process. The simulation of a system might not produce solutions close to the best available configuration, especially from an economic point of view. The result is often that at least one significant constraint is not satisfied.

Cost estimation is an essential ingredient in the process of creating support for business decisions within manufacturing operations and costing data must be integrated in the decision-making processes, so that economically sound decisions can be made (Liebers and Kals, 1997). Costing for decision support is useful for the improvement of performance, value creation, and scenario analysis, as well as the effective and efficient application of resources within an enterprise (Von Beck and Novak, 2000).

Every action or cessation of action in an organisation consumes economic resources and understanding how profits and value are created can be gained through costing (Professional Accountants in Business Committee, 2008, 2009). This is a way of understanding how efficiently and effectively input is transformed to output by operational processes. Information from costing can be used to analyse past performance and to analyse, motivate and influence future performance. One of the building blocks of costing is the measurement of consumed resources, in order to enable managers to make judgements about the financial impact of business decisions for future planning and the evaluation of available courses of action. This is the essential information for decision support leading to the efficient application of processes and resources in an enterprise. However, the Professional Accountants in Business (PAIB) Committee also states that a deeper diagnostic insight into the causes of events and a clear, direct connection to operations and the evaluation of options are usually required in the need for decision support. It is important to know why events happened and to be able to evaluate options for change. It is also essential to distinguish between costing to drive improved organisational performance and cost accounting to apply the technique that best evaluates and reveals the information required to select an alternative choice. Financial accounting for enterprises is generally divided into three branches, namely, tax, financial, and managerial accounting. The first two are historical, while the third is predictive and thus higher value-added for managerial decisions. Managerial accounting is related to planning and decision support and extends to incorporate non-financial data. The main purpose of cost analysis related to managerial accounting is to evaluate and understand the historical cost behaviour, in order to influence future events.

Nevertheless, cost analysis alone is not enough to support decision-making in the development of production systems. Expertise from other disciplines, such as industrial engineering and operation management, is required to support decision-making based on both costing and operational information. While excellence in manufacturing is often a result of a combination of successive incremental improvements and investment in technology or equipment, there are studies indicating that some organisations actually experienced losses in productivity, due to investment in manufacturing technology (Sim, 2001). The expectations of performance improvement from mere capital investment evaluations are often in the form of “quantum leaps”. Larsson et al., (2008) refer to incremental improvement and radical improvements and then introduce the concept of system boundary expansion. The idea is to increase the cost base through strategic expansion and work in the field of operational improvements on the larger cost base of the expanded system.

As a part of the cost estimation for product pricing, manufacturing cost can be divided into prime cost and factory expense (Hitomi, 1996). Prime cost can be further divided into direct material and labour cost and direct overhead, while factory expense includes indirect material and labour cost and indirect overhead. Depending on the options to be studied using a cost model for production system analysis, a selection of the cost categories must be included.

A state of the art survey on the current methods and processes of cost modelling, recently presented by Agyapong-Kodua et al., (2011), has revealed the limitations of the cost modelling techniques found in the literature. Based on their literature review, a number of requirements that need to be satisfied by a comprehensive cost modelling methodology are presented and briefly summarised as follows:

- Ability to capture effects regarding multiple products including mix of products.
- Translation of design solutions into equivalent manufacturing processes, sequences and resources.

- Ability to trace costs to specific products and processes, with cost estimation capturing the effect of various alternatives for process configuration.
- Incorporation of a virtual tool for cost model experimentation useful for evaluating design options, business ideas, reconfiguration or improvement of production systems.
- Characterisation and modelling in modular forms in order to facilitate the reuse of models.

They concluded that the integrated use of concepts from cost engineering, enterprise modelling, system dynamics modelling, and discrete event modelling provides crucial ingredients for compiling a cost model for decision support related to design and manufacturing.

One of the guiding principles for a cost model is to provide adequate cost estimations based on a minimum amount of information (Liebers and Kals, 1997). According to Needy et al., (1998), a cost model that attempts to include all cost factors tends to disallow both the collection of such data and the proper usage of such data in decision-making. However, there are several examples of methods and models, such as cost deployment (Yamashina and Kubo, 2002) and a general economic model for manufacturing cost simulation (Jönsson et al., 2007), requiring in-depth data mapped bottom up in a production system. Some examples of available approaches to overcome pitfalls due to data complexity are time-driven ABC (Kaplan and Andersson, 2007) and the cost of capacity concept (CMA Canada, 1999), including several tools and techniques within a framework for analysing capacity cost management issues, for example, the time-based resource effectiveness model. In another time-based approach, associating cost with factory cycle time (Rust, 2008), based on Little's Law (Little, 1961), there is the suggestion to use the relationship between the length of time in production and the overhead cost of the factory and/or capital cost of equipment supporting higher WIP levels. A strong basis for analysis and decision-making that can

be integrated in capital investment models is created by combining operational and financial data. Analysis results from time-based methods can be translated to financial data with a process costing model. There are similarities between the resource effectiveness model and LM (Nord and Pettersson, 1997 and Pehrsson, 2009) with corresponding data used in industry. One of the major key performance indicators used in loss models is OEE that directly links with critical financial ratios (Hansen, 2002). The benefits from an improved OEE can be realised in different ways depending on the situation. The same number of products can be produced in a shorter time, or if more products can be sold, a larger amount can be produced in the same time. According to Hansen, the saving in the first scenario is related to the saved cost due to reduced time for production. In an assembly system, the result is mainly a reduction in direct labour expense and, in many cases, it is actually due to reduced overtime, with even larger monetary effect. In the latter scenario, the benefit mainly comes from increased operating income related to the growth in sales.

4.2 Industrial Cost Modelling Theories

The cost model for production systems optimisation, proposed in this thesis, is designed to be integrated into a framework for decision-making empowered by SMO within manufacturing enterprises. The remainder of this chapter is organised as follows: the proposed cost modelling technique is described, then the integration of the cost modelling into production simulation and SMO procedures is introduced and followed by a complete hypothetical case study, including the MOO problem, optimisation results, data analysis, and the decision-making process. Finally, conclusions based on the results of this case study and those of a previous real-world industrial study are drawn.

The proposed cost model should enable the analysis of various production line design options and possible improvements from a financial perspective, in order to support decision-making. One important design criterion in the development of the overall

method is the ability to create support for conceptual, production system decisions. In such applications, the lead-time for modelling and data collection is limited due to the iterative and innovative nature of the early concept phase of a production system (Jägstam, 2004). Focus is often on generating decision support as fast as possible with adequate simulation quality (Jägstam and Klingstam, 2002), although a high level of detail would require a thorough understanding of the system and mature input data not available in early phases. Still, there is a requirement for fairly accurate estimations on a number of input parameters, including both technical and financial parameters, for the models to be satisfactory in supporting decision-making. The lead-time for data collection might be reduced by a common back-office process securing prepared production system data. In addition, as shown by Jägstam and Klingstam, (2002), there is a need for a structured way of implementing simulation tools into the company specific models for the development of manufacturing systems.

The proposed modelling technique requires the translation of product design options into manufacturing design options as a prerequisite, since the method will not allow design options to be directly translated to production or product cost. On the other hand, the evaluation of such options or scenarios will provide information on production costs related to various manufacturing design options. Hence, the method could be used as one step in the process of establishing relations between product design and pricing, or to search for trade-offs fulfilling market requirements.

There are a number of parameters connected to the modelling of the production system itself. The most significantly detailed ones are cycle times in machines, automation cells, and assembly stations, together with the availability and MDT for these components of the system. With the addition of flow logic, control logic, staffing schedules, buffering capacities, and dispatching rules, the production system itself can be modelled with sufficient accuracy, in order to predict performance on lead time and throughput (Ng et al., 2007).

One essential factor to consider for decision-making with regard to production systems is the estimation of the running cost. Average throughput over time is a major factor to consider when estimating the running cost, due to its close relation to the utilisation of the system. With increased throughput, the time used for production can be reduced or, alternatively, more products can be produced in the same amount of time, which indirectly reduces the running cost.

The performance of the production system and the utilisation of resources can be aggregated into the running cost through a budget analysis and compilation of hourly cost factors, in order to support marginal or incremental decisions. This is preferably executed as a back-office process so that it serves as one of the prerequisites for a quick decision-making and manufacturing management process. A number of parameters need to be included in the preparation of accurate cost estimations. Current research has identified such parameters and data requirements in conceptual bottom-up information (Roy et al., 2011). The actual parameters used in real-life studies might vary depending on the business and the objectives to be analysed. A generic systematic approach should enable the use of similar methods with the assistance of a company's financial analysts (Hansen, 2002).

In order to reduce the information requirement and to limit the number of cost factors included, the proposed approach uses an aggregated level of information to estimate the effect of incremental changes to a system. This enables the analyst to use an initial running cost based on accounted values for a cost centre, as a starting point. When applied on conceptual production systems, an initial running cost for a specific state of the system can be estimated through a conceptual budget. Estimations of the cost per hour, in the form of hourly cost factors for a system within certain intervals of throughput, enable the translation of throughput from a simulation model to a monetary effect on the system. The same type of approach, based on calculating the value of saved production time, is proposed when applying an OEE improvement strategy (Hansen, 2002). The estimated hourly costs are just valid in certain intervals. One essential factor can be deviations in staffing requirements, depending on the production

system's throughput and the capacity demand (Andersson et al., 2009). Another example of this is staffing templates based on time setting and line balancing data found within industry, stating the balanced staffing requirement for an expected throughput and salary cost in relation to throughput, graphically presented in Figure 4.1. In order to meet fluctuations in customer demand, various levels of throughput can be achieved by the alignment of the number of operators working on the line. That is, the throughput can be throttled by reducing the staffing according to the template specific for the line. Note that the cost differs between various shift patterns, which can also be related to throughput intervals depending on the customer demand.

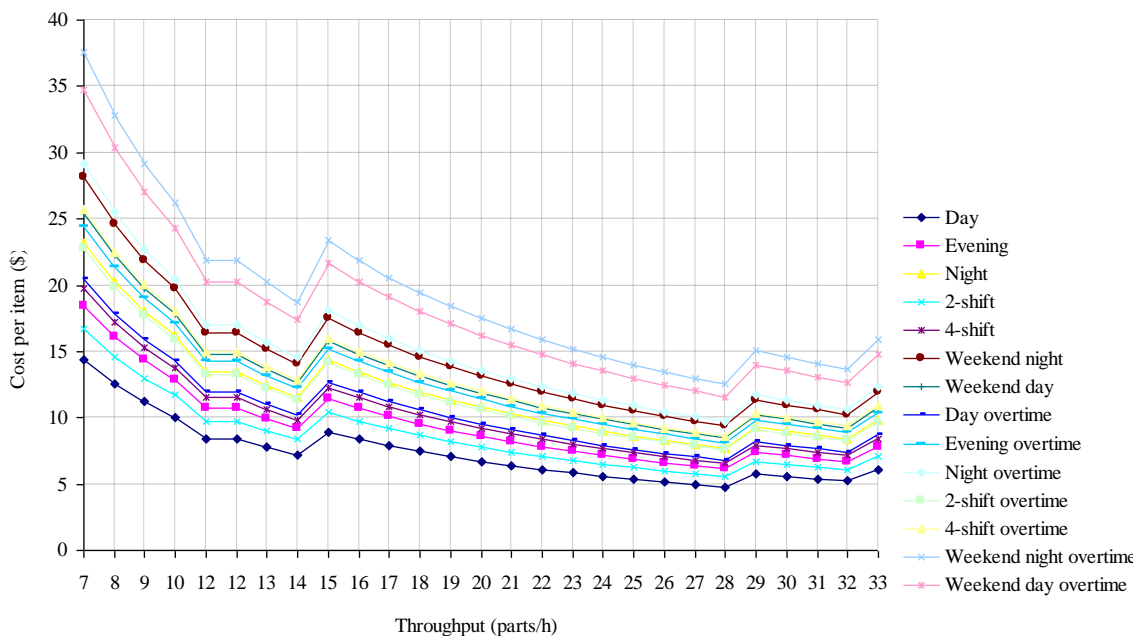


Figure 4.1. Example of salary cost in relation to throughput from a real-world machining factory.

An important factor to consider is how the capacity alignment to customer demand is performed. Specifically, it is interesting to investigate whether the staffing and the reduced throughput occur over all shifts or only during one of them. It is considered a benefit to keep the pace up and run the system at a high throughput for the longest possible proportion of time, in order to reduce losses due to the low utilisation of

machines, facilities and operating hours (Sakamoto, 2010). One way of doing this is to maximise production speed and reduce staffing for one shift, when levelling production to customer demand. This could also be important, when maintaining the ability to produce at full speed in a line is considered.

Annual data is used in order to correspond with forecasts, budget, and accounting values. When this part of the running cost model is integrated with a simulation model, the incremental effect corresponding to various options and scenarios influencing throughput can be studied from a financial perspective.

4.3 An Incremental Cost Modelling Method

In its most basic form, the cost model principle is described by:

$$\xi_R = \xi_I + \Delta\xi \quad (4.1)$$

where ξ_R = Running cost per year (annual running cost), ξ_I = Initial running cost per year, and $\Delta\xi$ = Incremental cost per year.

Based on the cost of resources for running the production, a cost per hour is calculated and the reduced time required for production is calculated from the increased throughput, defined step by step below.

The difference in required production time is multiplied by the cost per hour.

$$\Delta\xi_T = \tau \times \xi_H \quad (4.2)$$

where $\Delta\xi_T$ = Throughput delta cost, τ = Difference in required production time, and ξ_H = Cost per hour (additional time) corresponding to “capacity cost rate”

The difference in required production time can be calculated as:

$$\tau = \tau_A - \tau_I \quad (4.3)$$

where τ_A = Time required for production of annual production volume and τ_I = Initial time required for production of annual production volume

The calculation of the difference in required production time is based on the difference in throughput for an annual production volume.

$$\tau = \frac{V_A}{\varphi} - \frac{V_A}{\varphi_I} \quad (4.4)$$

where V_A = Annual production volume, φ_I = Initial Throughput, φ = Throughput

By simplifying the above expression:

$$\tau = V_A \left(\frac{1}{\varphi} - \frac{1}{\varphi_I} \right) \quad (4.5)$$

The variable cost per hour can be based on several components, including energy consumption, coolant consumption, labour costs, and so on. By multiplying the difference in required production time by the cost per hour for running the production system, the incremental running cost due to throughput difference can be calculated. This cost is dependent on the operation to be analysed and can be described by a delta throughput to cost function:

$$\Delta \xi_T = \xi_H V_A \left(\frac{1}{\varphi} - \frac{1}{\varphi_I} \right) \quad (4.6)$$

The cost per hour may, however, be dependent on throughput, and it is essential to consider how to include such a dependency in the estimation. One portion of the cost per hour can be referred to as fixed cost and is already included in the initial running

cost, ξ_I while the other portion can be referred to as variable cost. The variable cost could be linear or polynomial. If the variable cost is linear in relation to throughput, the cost per hour can be written as:

$$\xi_{H_i} = \xi_{H_{a_i}} + \xi_{H_i}' \varphi \quad (4.7)$$

where $\xi_{H_{a_i}}$ = the variable cost at the start of the interval i and ξ_{H_i}' = gradient (slope) of ξ_{H_i} within the interval i , i = throughput interval.

Hence, very precise predictions can be made by replacing ξ_{H_i} with an appropriate function, if such a function is known and the required data is available. Another approach is to use some kind of abstraction, in order to reduce the demand of finding a function and the data requirements. Depending on the throughput interval width studied, the production system design and the applied operational strategy, the difference in variable cost per hour between the lower throughput limit and the higher throughput limit is likely to be much smaller than the total cost per hour. In such cases, an abstraction can be made by calculating an average cost per hour for the throughput interval.

Recall that since a specific $\Delta\xi_T$ might only be valid as an approximation within a specific interval, it may be necessary to introduce several $\Delta\xi_T$ -functions, in order to create a complete model, due to constraints in the production setup, e.g., balancing staffing or different costs for various shifts. With the proposed method, it is possible to work with abstracted data by specifying a number of intervals, in order to correctly estimate and map the system's response to changes and the resulting cost behaviour of the reduced input data requirement. The data collection and preparation effort needed with this method is dependent on the nature of the system studied, the expected accuracy and the studied throughput range. The throughput to cost function for an interval with data abstraction can be written as:

$$\Delta \xi_{T_i} = \bar{\xi}_{H_i} V_A \left(\frac{1}{\varphi} - \frac{1}{\varphi_{I_i}} \right) \quad (4.8)$$

where $\bar{\xi}_{H_i}$ = average cost per hour for throughput interval i and φ_{I_i} = the initial throughput at the lower end of the throughput interval i .

valid for a certain throughput interval

$[a_i, b_i]$, i.e. $a_i < \varphi < b_i$

An example of the difference in accuracy between the detailed calculation of ξ_{H_i} for each discrete throughput step and the abstracted calculation of $\bar{\xi}_{H_i}$ with throughput intervals is shown in Figure 4.2. The step effects seen in this example come from balancing the number of workers dependent on the planned throughput. The maximum running cost deviation in this example is less than $\pm 4\%$, as shown in Table 4.1, and can be improved by calculating the cost with narrower throughput intervals.

Table 4.1. Deviation between abstracted and detailed running cost estimation.

Interval	Beginning (b) and end (e) of interval	Running Cost (\$)		Deviation = (Abstracted-Detailed) /Abstracted
		Abstracted estimation	Detailed estimation	
1	b	4320224	4159509	3,72%
1	e	3292324	3417324	-3,80%
2	b	3772176	3650189	3,23%
2	e	3162825	3235586	-2,30%
3	b	3712910	3619509	2,52%
3	e	3205402	3272366	-2,09%

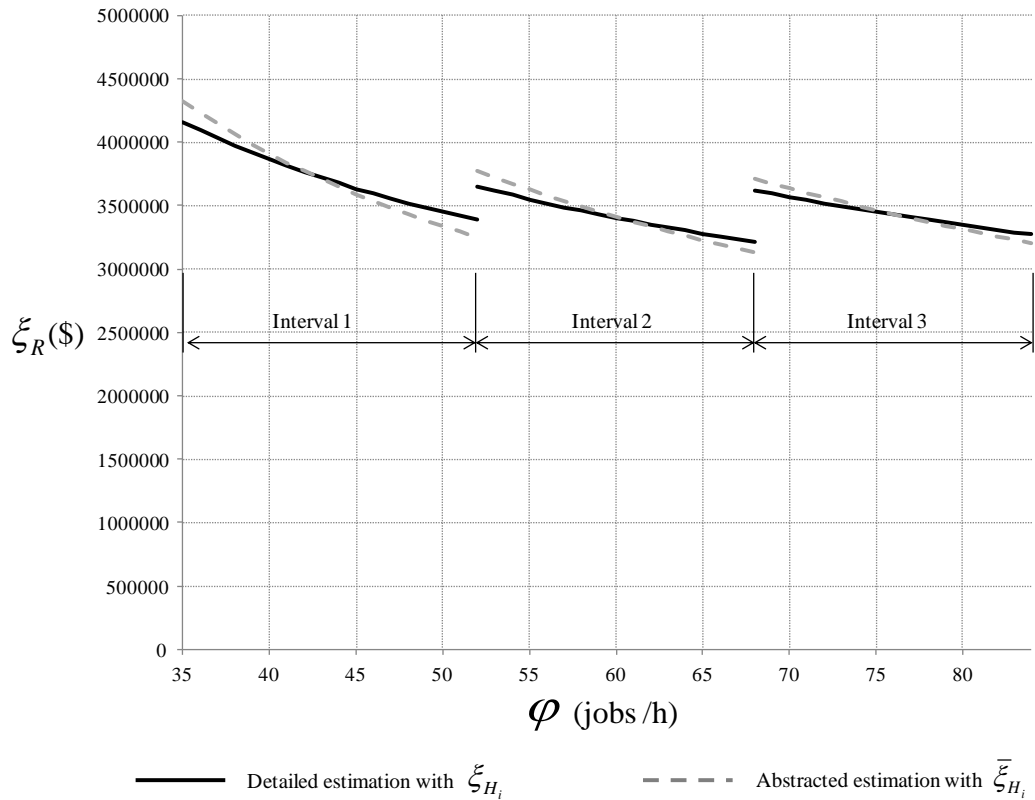


Figure 4.2. Detailed vs. abstracted running cost estimation.

The complete incremental throughput cost is then:

$$\Delta \xi_T = \sum_{i=1}^m \Delta \xi_{T_i} \quad (4.9)$$

where m = the number of throughput intervals.

When setting up a cost model for production system development or improvement, it is imperative to consider the use of fixed and variable costs. Furthermore, when investing or introducing changes in a production system, it has been observed in many industrial cases that the variable costs are affected by, e.g., changed throughput. However, when selecting among alternative methods and production design options, fixed costs may also be affected. In that case, a specific alternative influences the fixed cost and can be included in the model as an annual expense.

Each improvement can have a number of such incremental costs attached and could also reflect, e.g., maintenance or infrastructure cost deltas. When integrated in simulation models for production systems analysis, each such incremental cost must be included as a total sum.

Incremental annual cost function:

$$\Delta \xi_A = \sum_{j=1}^n \Delta \xi_{A_j} \quad (4.10)$$

where n = the number of incremental annual cost parameters in the simulation model.

There may also be a change in the cost per produced item, due to the performed changes, e.g., consumption of cutting tools, welding tips, incoming material, and energy use. All differences in the cost per unit should be mapped into the simulation model and included in a total sum.

Delta cost due to changed cost per produced unit function:

$$\Delta \xi_U = \sum_{k=1}^o \Delta \xi_{U_k} v_A \quad (4.11)$$

where o = the number of cost per unit parameters in the simulation model.

The combination of the cost effects induced by all the incremental or combined improvements applied on the production system formulates the total running cost function. In order to enable tailored applications, a customised cost component is added to the resulting expression.

The complete annual running cost function:

$$\begin{aligned} \xi_R = & \xi_I + \sum_{i=1}^m \Delta \xi_{T_i} + \sum_{j=1}^n \Delta \xi_{A_j} \\ & + \sum_{k=1}^o \Delta \xi_{U_k} v_A + \Delta \xi_C \end{aligned} \quad (4.12)$$

where, $\Delta \xi_C$ = user definable custom cost component.

The annual running cost expression in its simplified form becomes:

$$\xi_R = \xi_I + \Delta\xi_T + \Delta\xi_A + \Delta\xi_U + \Delta\xi_C \quad (4.13)$$

Among industrially applied analysis methods in general, there are no easy ways of finding the right combinations of minor improvements, investments and settings for the various dynamic system parameters of a production system targeting the performance and the resulting running cost. It can be a daunting task if the best trade-off or a combination of actions to improve several conflicting objectives has to be found. Based on the experience of the data collected from industrial case studies within machine-intensive component manufacturing, the common level of industrial data available for scenario description is up-time, processing time, and improvement cost or investment required for local improvement. In some cases, there might also be data describing the mean time to repair (MTTR), or MDT, for machines, stations, or production cell level.

The local effect on, e.g., the processing time achieved by a specific improvement with a defined cost is rather well known within a mature manufacturing organisation. For example, a specific improvement of component A in operation B will increase the up-time X%. However, on many occasions, improvements are introduced without the possibility to analyse and optimise the impact from a combination of activities. An even worse scenario is when the wrong action is applied due to a lack of knowledge with regard to prioritising among vast amounts of options. The running cost function alone cannot solve this issue without investment data mapped to relevant scenarios in a simulation model. In order to enable the simultaneous optimisation of investments and running cost, a number of parameters must be incorporated into the simulation model.

The suggested solution is to map and index changes in processing time and up-time to certain objects in the simulation model in a discrete number format. The index number for each improvement linked to an object can then be related to a certain investment and the complete investment can be calculated, in order to be used as an optimisation objective. Each solution generated during optimisation will be a combination of

individually prepared improvements with linked costs and investments. These costs and investments are summed in order to calculate the total cost and investment for the specific solution.

The impact of investments related to processing time can be written as:

$$\lambda_{\alpha} = \sum_{i=1}^m \lambda_{\alpha_i} \quad (4.14)$$

where, λ_{α} = processing time related investments and m = the number of the number of parameters related to processing time.

The impact of investments related to up-time can be written as:

$$\lambda_{\beta} = \sum_{j=1}^n \lambda_{\beta_j} \quad (4.15)$$

where, λ_{β} = up-time related investments and n = the number of parameters related to up-time.

Another factor with a potential effect on the production system performance is buffer capacity and buffer allocation. If there are certain investments related to changes in buffer capacity, they can be modelled in the same way as processing time or up-time related investments:

$$\lambda_B = \sum_{k=1}^o \lambda_{B_k} \quad (4.16)$$

where, λ_B = buffer capacity related investments and o = the number of parameters related to buffer capacity.

In order to enable tailored applications, a custom investment component is added to the resulting expression. The complete investment function for integration in a simulation model can be expressed as:

$$\lambda = \sum_{i=1}^m \lambda_{\alpha_i} + \sum_{j=1}^n \lambda_{\beta_j} + \sum_{k=1}^o \lambda_{B_k} + \lambda_C \quad (4.17)$$

where, λ = total Investment, λ_c = user definable customised investment component

Following is the total investment expression in its simplified form:

$$\lambda = \lambda_\alpha + \lambda_\beta + \lambda_B + \lambda_c \quad (4.18)$$

The λ_c component is intended for the addition of other investment categories such as sustainability related investments. It could also be used to separate amortised from non-amortised investments (improvement costs). When integrated into a simulation model that includes all the modelling components, the cost model can cover the analysis of a wide range of improvements on a production system. In order to apply the model in a nimble way, especially during the concept phase of a production system, it is essential to set up a process for acquiring data in advance. Another imperative success factor is to reduce the included number of cost model components and objectives accordingly and focus on the ones most important for decision-making. It is vital to remember that the throughput performance data for the cost model expressions comes from the simulation model, which enables the objective function evaluation to be performed.

However, it is not always easy to capture the cost effect of all changes to a production system. One parameter that can be difficult to estimate is the individual running cost of buffers. If such a factor is known, it can be incorporated into the cost model through the ordinary parameters. However, it is also a common practice to consider the buffering in a system as a separate optimisation objective, i.e., to minimise the total buffer capacity necessary and sufficient to attain a desired throughput. This objective can be called Lean level of buffering or simply lean buffering (Enginarlar et al., 2005). In that case, the sum of all buffers in the production system can be calculated according to:

$$Bc = \sum_{i=1}^m Bc_i \quad (4.19)$$

where m = the number of buffers subject for optimisation.

By introducing the total number of buffers as an optimisation objective, such a parameter can be optimised together with the cost, sustainability, and other production system metrics. Other expenses, such as those for set-up and quality handled by other cost models (Agarwal, 2007, Needy et al., 1998) can also be integrated by incorporating such events in the simulation model and connecting them to the cost model.

4.4 Integration of Cost Modelling into Optimisation

To fully utilise all the benefits of the cost model, it should be integrated with simulation and a heuristic search method, enabling optimisation towards the fulfilment of several conflicting objectives.

In order to perform optimisation of the financial impact from investments in a production system with the suggested method, a valid simulation model of the production system is required. It is highly recommended that the model abstraction level is aligned with the available data and the prerequisites of the decision situation. There are some questions that need to be answered when considering the model abstraction level. Is the analysis to be made in the conceptual phase, during implementation of production updates, or is it made during running production? What level of decision is to be made and which are the main objectives that should be met? Are there any limitations in lead time, available resources or data until the point of decision? Most likely, there are such limitations in most situations within common industrial operations.

It is desirable to avoid pitfalls regarding overly complex modelling and very detailed data. Requirements for data that is difficult to collect should be avoided. In addition, to facilitate a short lead-time for the creation of decision support, an easy-to-use modelling environment with built-in data complexity reduction, targeting the system level of production operations, will facilitate the creation of models with a balanced abstraction trade-off.

During optimisation, the input parameters must be altered in the simulation model for every iterative evaluation run. In a SBO application, these parameter changes can be made automatically by connecting an optimisation algorithm to the simulation model. The connection enables the optimisation engine to directly change the variables in the simulation model, so that an optimisation solution, represented as a combination of parameter settings, can be evaluated as an improvement alternative. Every object in the simulation model that will be directly affected by investments or improvements is therefore the subject of an improvement alternative selection. The principle of an improvement alternative table for cost and parameter values is shown in Table 4.2.

Table 4.2. Improvement alternative table for an object in the simulation model.

Improvement alternative	Parameter X	Parameter ...	Parameter n	λ_{α}	λ_{β}	λ_B	$\Delta\xi_A$	$\Delta\xi_U$
0	A	...	α	$\lambda_{\alpha a}$	$\lambda_{\beta a}$	λ_{Ba}	$\Delta\xi_{Aa}$	$\Delta\xi_{Ua}$
1	B	...	β	$\lambda_{\alpha b}$	$\lambda_{\beta b}$	λ_{Bb}	$\Delta\xi_{Ab}$	$\Delta\xi_{Ub}$
...
n	N	...	ν	$\lambda_{\alpha n}$	$\lambda_{\beta n}$	λ_{Bn}	$\Delta\xi_{An}$	$\Delta\xi_{Un}$

The proper parameter value can be selected from the cost parameter value table, by adding an optimisation parameter for the actual improvement alternatives to be simulated in specific optimisation iterations. In the simulation software, the parameter value can be set from the table on the basis of an integer value for a specific improvement alternative controlled by the optimisation engine. Scenario 0 corresponds to the initial solution with no improvements applied. The principle of simulation model integration is illustrated in Figure 4.3.

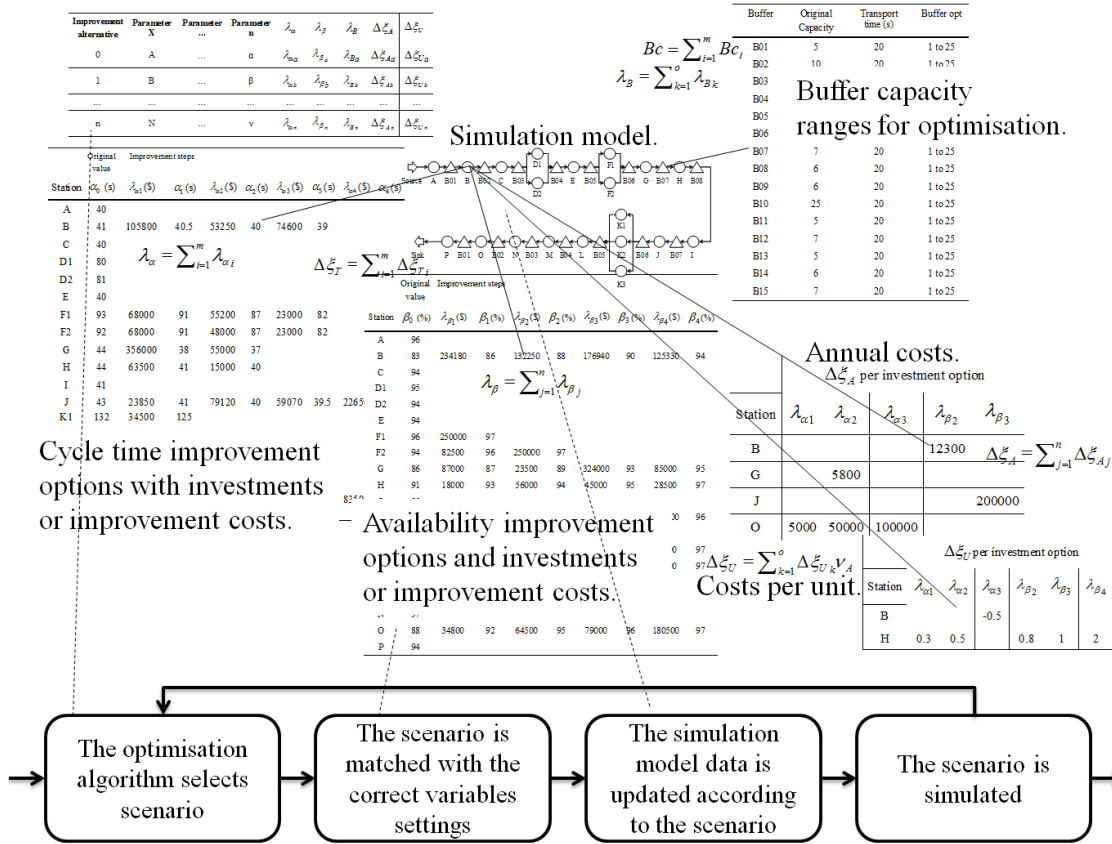


Figure 4.3. Simulation model integration with the optimisation process.

The complete process of applying the cost and sustainability modelling can be compiled into a workflow that starts with preliminary objective setting, data collection, and simulation modelling, continues with bottleneck analysis or constraints identification, and includes optimisation, post-optimality analysis and visualisation as the key steps for decision support. The proposed workflow can be seen in Figure 4.4.

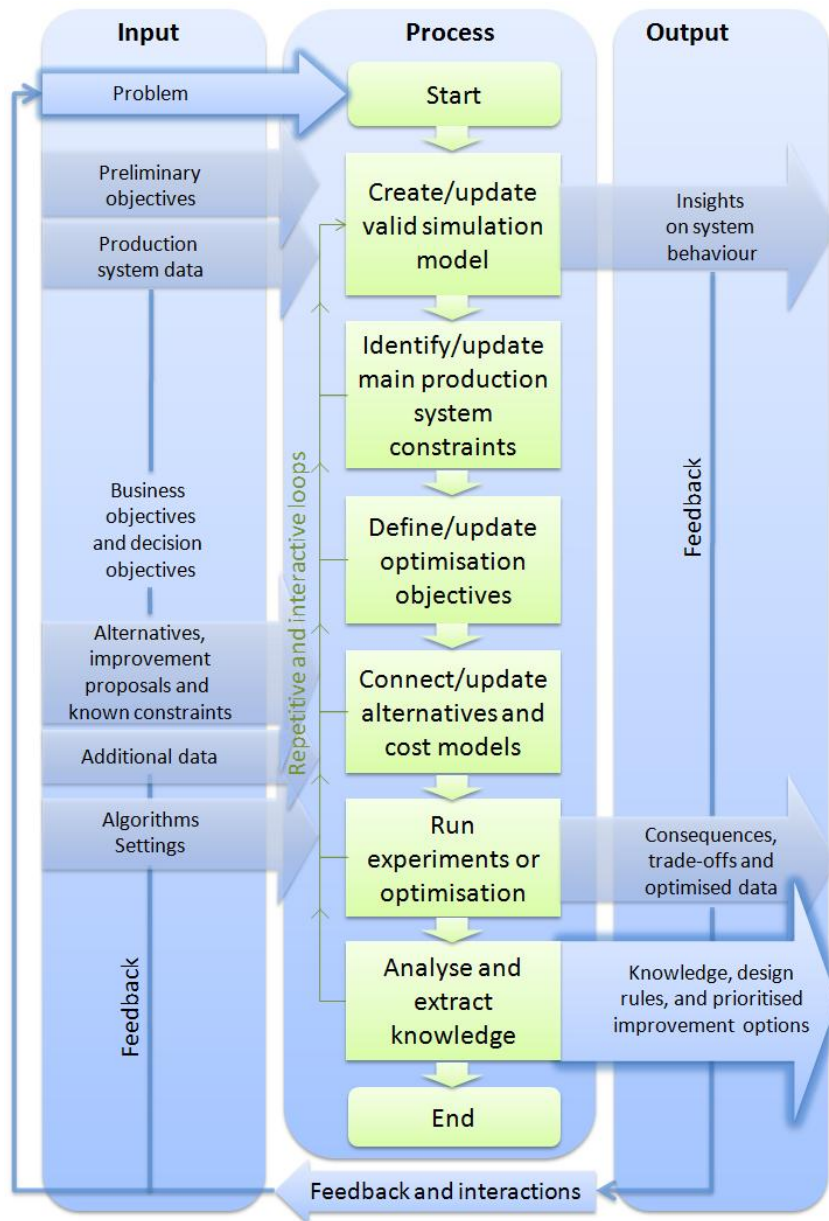


Figure 4.4. Cost optimisation workflow.

The cost modelling method has been tested and verified through both experiments, in this chapter, and industrial case studies, in Chapter 7, Section 7.2. The cost model has been integrated in DES models and production systems have been optimised using heuristic search methods with GA regarding objectives within the domains of cost sustainability and direct production system performance (Pehrsson and Ng, 2011).

4.5 Experimental study

An experimental study has been designed to replicate an industrial case study as much as possible, without revealing the original data and model details from the manufacturing company. In other words, the data and modelling details provided below have been modified from the original real-world case study to enable the same set of experiments to be repeated by other researchers.

It is necessary for a production line with capacity constraints to operate on overtime (e.g., night/weekend shifts), in order to meet the forthcoming increase in customer demand. There are a number of potential improvements that would entail various costs and investments that could reduce the capacity constraints. It should be possible to avoid operating the line on overtime. However, not enough information is available to make a decision to invest and reduce the operating time and the cost of labour and production resources.

The initially forecasted, annual running cost is \$3.6 million (M) and the main objective is to achieve a 22% running cost reduction with a total buffer capacity less or equal to 200. The challenge is to identify the optimal improvement alternatives that can reduce the running cost as much as possible, minimise the total cost of improvement, maximise throughput, and simultaneously minimise inter-workstation buffers. The initial total buffer capacity is 117.

The line consists of fifteen operations with inter-workstation buffers. Three of the operations are parallelised with two or three workstations each, as shown in Figure 4.5.

The running cost function involves the throughput to cost function, the annual cost function and the cost per unit function. The throughput to cost function has three intervals with a different hourly cost. For throughput values below 57, the average hourly cost ($\bar{\xi}_{H_1}$) is estimated to be \$610, for throughput values $57 < \varphi < 63$, the average hourly cost is estimated to be \$580 and for $\varphi \geq 63$, the average hourly cost is

estimated to be \$520. The annual costs and the values of the cost per unit function can be found in Tables 4.3 and 4.4.

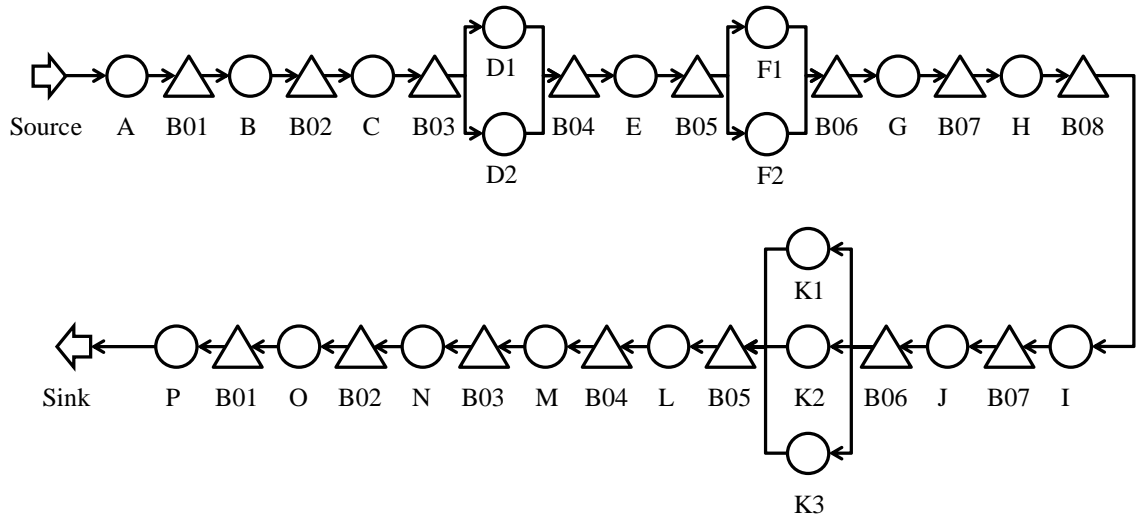


Figure 4.5. The experimental study line based on a real-world case study.

The initial simulation data and the improvement options can be found in Tables 4.3 and 4.4. The MDT for all workstations are set to 15 minutes. Buffer configurations and options for lean buffer optimisation are shown in Table 4.5. The transport times for all buffers are set to 20 seconds.

A first test simulation of the initial solution, with five replications, each simulating 30 days production plus one day for warm-up, resulted in a throughput of 54.1 parts per hour, a lead-time (factory cycle time) of 1.30 hours and a WIP of 70.3 parts. The accuracy of the simulation outputs can be verified by using Little's Law (WIP/Cycle Time = Throughput): $70.3 / 1.30 = 54.1$.

A shifting bottleneck analysis gives an indication of the bottleneck workstations that may require improvements (see Figure 4.6). The selected improvement alternatives to be included as optimisation parameters are shown in Tables 2, 3, and 4. Incremental annual costs ($\Delta\xi_A$) and incremental costs per unit ($\Delta\xi_U$) connected to some of the investment options (λ_{α_n} or λ_{β_n}) are shown in Tables 4.6 and 4.7.

Table 4.3. Original values for cycle time (α_0) and improvement options with costs and new cycle times (α_n).

Station	Original value	Improvement steps							
	α_0 (s)	λ_{α_1} (\$)	α_1 (s)	λ_{α_2} (\$)	α_2 (s)	λ_{α_3} (\$)	α_3 (s)	λ_{α_4} (\$)	α_4 (s)
A	40								
B	41	105800	40.5	53250	40	74600	39		
C	40								
D1	80								
D2	81								
E	40								
F1	93	68000	91	55200	87	23000	82		
F2	92	68000	91	48000	87	23000	82		
G	44	356000	38	55000	37				
H	44	63500	41	15000	40				
I	41								
J	43	23850	41	79120	40	59070	39.5	22650	38
K1	132	34500	125						
K2	134	52000	133	64000	132	34500	125		
K3	133	64000	132	34500	125				
L	41								
M	40								
N	41								
O	43	87960	41.5	56320	41	76250	40	83500	39
P	41								

Table 4.4. Original values for availability (β_0) and improvement options with costs and new availability (β_n).

Station	Original value		Improvement steps						
	β_0 (%)	λ_{β_1} (\$)	β_1 (%)	λ_{β_2} (\$)	β_2 (%)	λ_{β_3} (\$)	β_3 (%)	λ_{β_4} (\$)	β_4 (%)
A	96								
B	83	234180	86	132250	88	176940	90	125330	94
C	94								
D1	95								
D2	94								
E	94								
F1	96	250000	97						
F2	94	82500	96	250000	97				
G	86	87000	87	23500	89	324000	93	85000	95
H	91	18000	93	56000	94	45000	95	28500	97
I	95								
J	89	46380	92	37800	93	94520	95	156000	96
K1	92	42500	94	29000	95	65400	97		
K2	90	38700	92	42500	94	29000	95	65400	97
K3	90	38700	92	42500	94	29000	95	65400	97
L	95								
M	96								
N	97								
O	88	34800	92	64500	95	79000	96	180500	97
P	94								

Table 4.5. Buffer configurations.

Buffer	Original Capacity	Transport time (s)	Buffer opt
B01	5	20	1 to 25
B02	10	20	1 to 25
B03	7	20	1 to 25
B04	5	20	1 to 25
B05	4	20	1 to 25
B06	12	20	1 to 25
B07	7	20	1 to 25
B08	6	20	1 to 25
B09	6	20	1 to 25
B10	25	20	1 to 25
B11	5	20	1 to 25
B12	7	20	1 to 25
B13	5	20	1 to 25
B14	6	20	1 to 25
B15	7	20	1 to 25

Table 4.6. Incremental annual costs (in \$) as connected to some of the investment options.

	$\Delta \xi_A$ per investment option				
Station	λ_{α_1}	λ_{α_2}	λ_{α_3}	λ_{β_2}	λ_{β_3}
B				12300	
G		5800			
J					200000
O	5000	50000	100000		

Table 4.7. Incremental costs per unit (in \$) as connected to some of the investment options.

Station	$\Delta\xi_U$ per investment option					
	λ_{α_1}	λ_{α_2}	λ_{α_3}	λ_{β_2}	λ_{β_3}	λ_{β_4}
B			-0.5			
H	0.3	0.5		0.8	1	2

A shifting bottleneck analysis gives an indication of the bottleneck workstations that may require improvements (see Figure 4.6). The selected improvement alternatives to be included as optimisation parameters are shown in Tables 2, 3, and 4. Incremental annual costs ($\Delta\xi_A$) and incremental costs per unit ($\Delta\xi_U$) connected to some of the investment options (λ_{α_n} or λ_{β_n}) are shown in Tables 4.6 and 4.7.

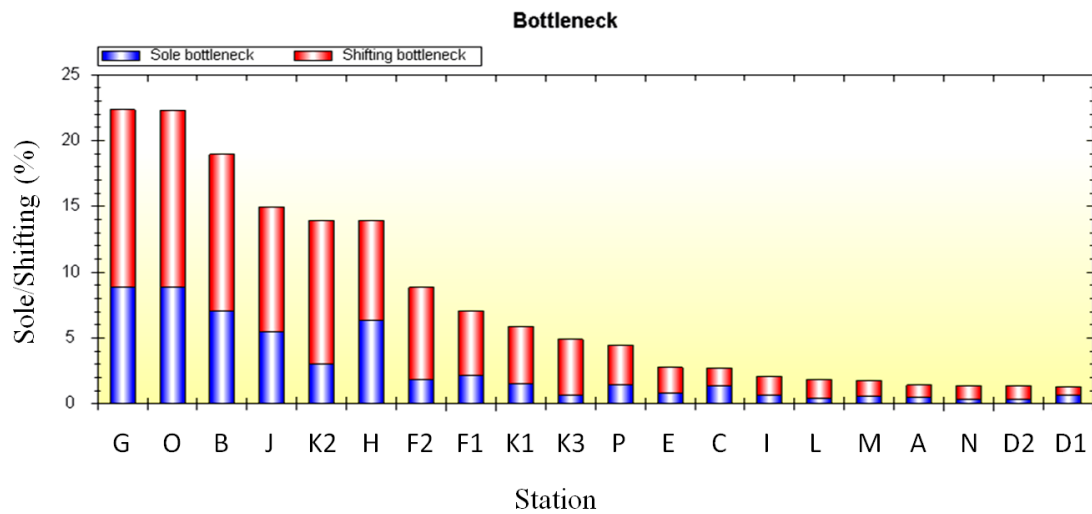


Figure 4.6. Shifting bottleneck analysis.

An optimisation comprising 20,000 iterations with 5 replications each was run using the NSGA-II algorithm (Deb 2001). The non-dominated solutions are plotted in Figures 4.7, 4.8 and 4.9.

One interesting observation that can be made is that the running cost for the system can be reduced from \$3.6M to approximately \$3.1 M without any investment. This is possible by the reconfiguration of buffer capacities. However, with the introduction of investments (or improvement costs), the running cost can be reduced, while the buffer capacities are kept at comparably lower levels.

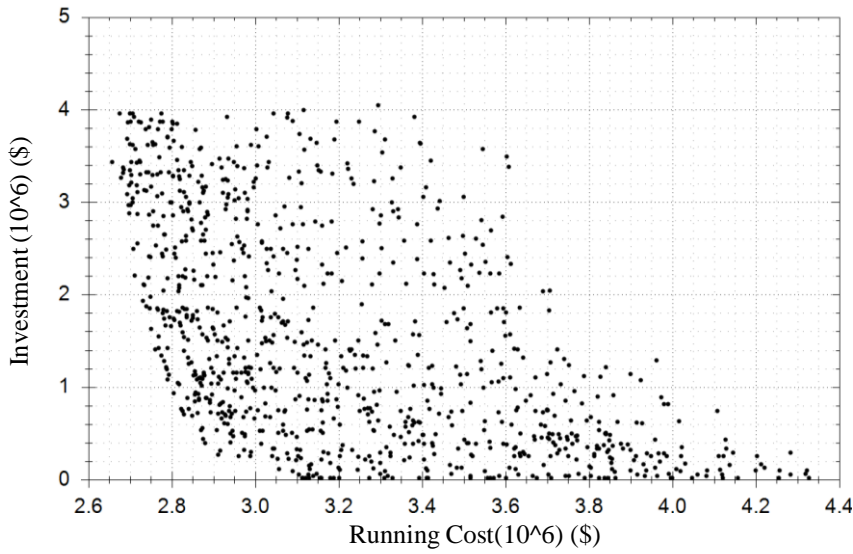


Figure 4.7. Non-dominated solutions for running cost and investment.

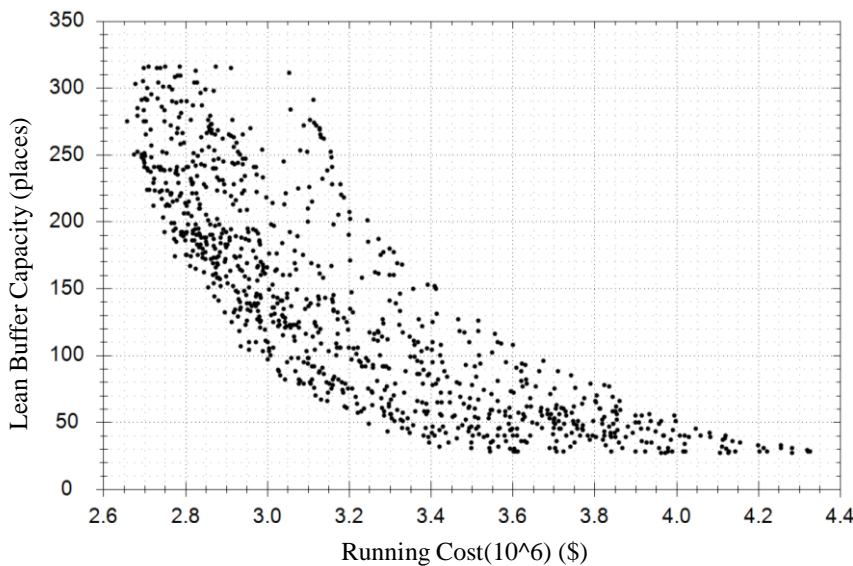


Figure 4.8. Non-dominated solutions for running cost and lean buffer configurations.

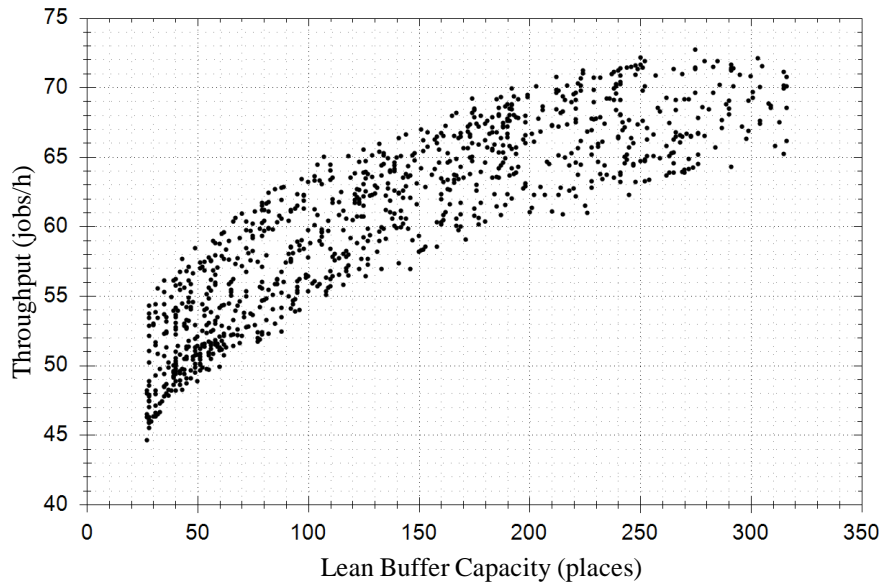


Figure 4.9. Non-dominated solutions for lean buffer capacity and throughput.

If we consider the main target, i.e., a 22% reduction of running cost, which corresponds to achieving \$2.8M, while studying the Pareto fronts from the optimisation, the Lean buffer sum must be larger than approximately 170, in order to be able to meet the running cost target. At the same time, Figure 4.7 reveals that more than a \$1M investment is required if a 22% or more running cost reduction is desired. However, when the optimisation results were examined more carefully, it was found that none of the solutions can achieve those figures simultaneously. Obtaining a solution meeting both the target of a 22% running cost reduction and the lean buffer target of 200 will require at least a \$3.01M investment. In fact, there are only thirteen solutions on the Pareto front fulfilling the running cost and lean buffer targets simultaneously, as shown with data filtered according to decision maker preference in Figure 4.10. These solutions demand comparably large investments and it is apparent that some kind of trade-off is required in order to make a decision.

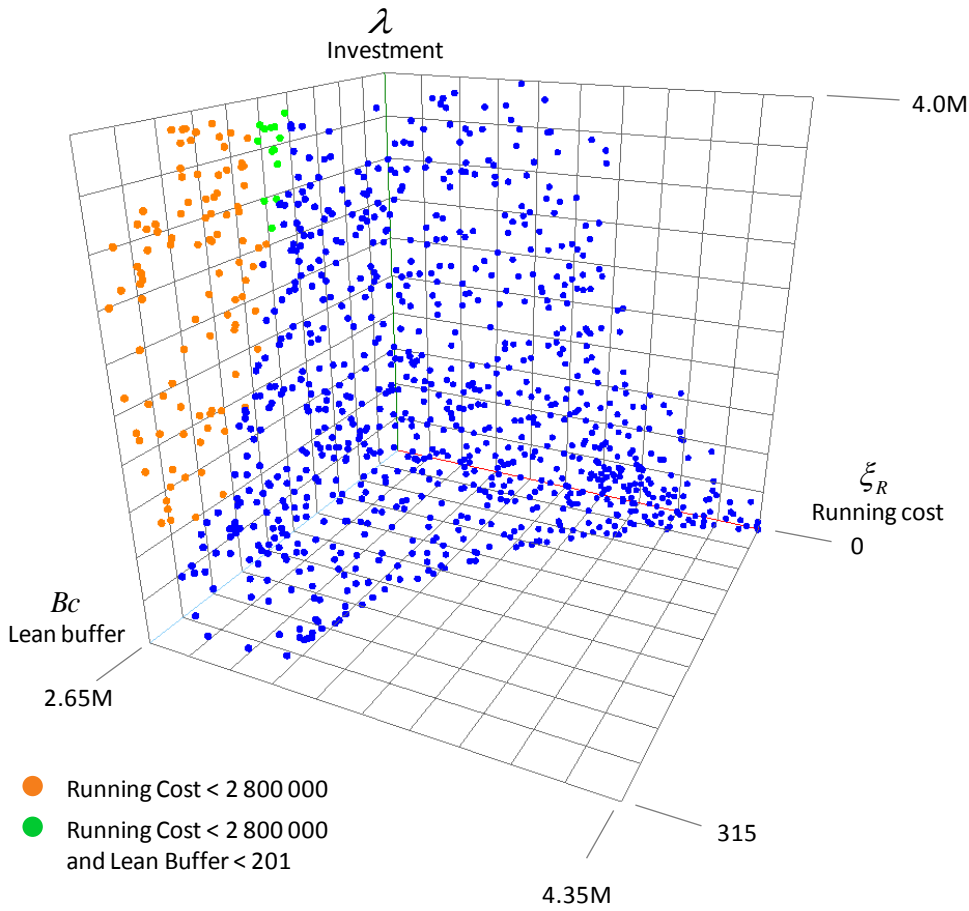


Figure 4.10. Non-dominated data filtered according to decision-maker preference.

It is therefore important to perform some extended post-optimality analysis on the optimisation data, in order to help the decision maker consider, for instance, pay-off time and rate of return on investment as additional factors in the decision-making process. In this example, we only consider pay-off time. Figure 4.11 shows a colour-coded 3D data plot (4D) in which the colour divides the Pareto-optimal solutions according to their pay-off times. The formula used to filter out various pay-off times is shown below:

$$PayOffFilter : \frac{(InitialRunningCost - RunningCost) \times PayOffTime}{Investment} > 1 \quad (4.20)$$

Depending on the pay-off time requirements, various parts of the data will satisfy the decision criteria. With a one year pay-off requirement on investments, the running cost target cannot be met. However, there are some reasonably good solutions that do not deviate too much from the target. For example, investing \$0.53M in combination with a lean buffer sum of 198 could lower the running cost to \$3.01M, which corresponds to a 16.4% cost saving (referred to as solution A). If two years pay-off time and some additional buffers could be allowed, there is, e.g., a solution with a \$1.54M investment and a total buffer capacity of 234 that results in the running cost of \$2.83M (referred to as solution B). These two solutions and their parameter settings can be seen in Table 4.8. This is one way of finding solutions and trade-offs for decision-making.

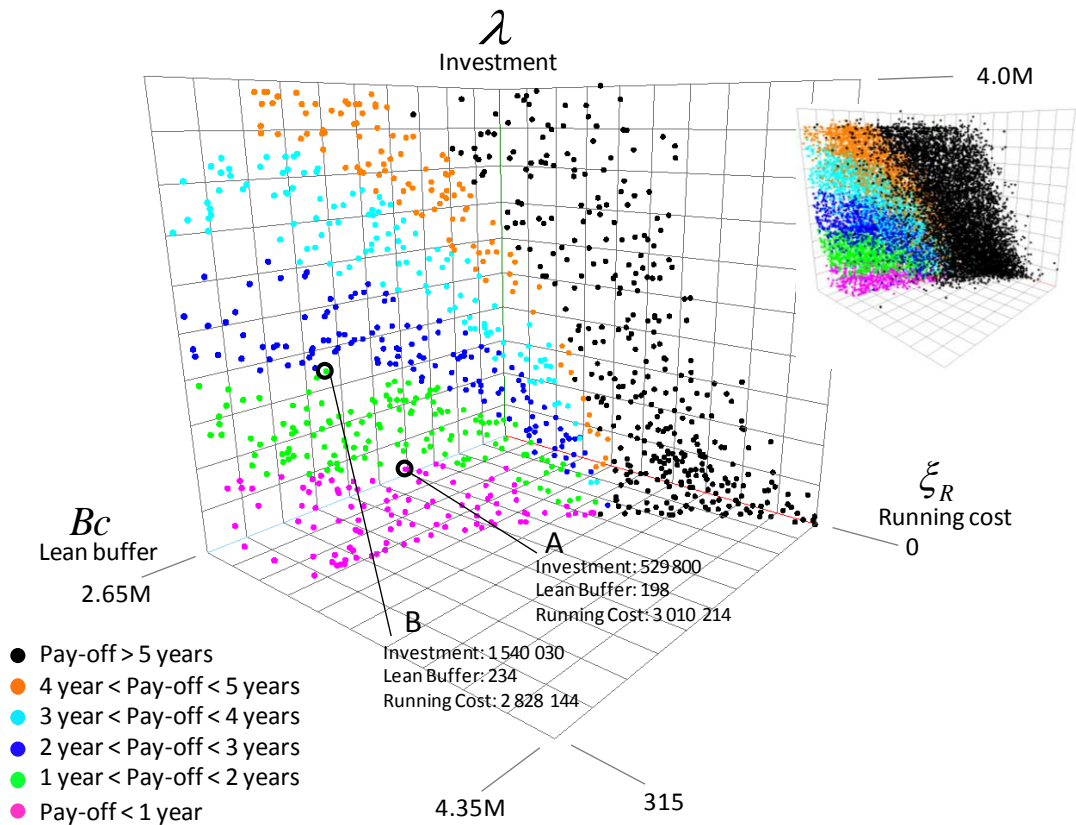


Figure 4.11. Main 4D-chart: Non-dominated solutions with pay-off time regions and discussed decision-alternatives. Upper right 4D-chart: Complete data set from optimisation with pay-off time regions.

Table 4.8. Solutions A and B with their objective values and parameter settings.

Parameter	Solution A	Solution B	Parameter	Solution A	Solution B
φ	62.89426184	67.40048701	λ_{β_B}	0	0
λ	529800	1540030	$\lambda_{\beta_{F1}}$	0	0
Bc	198	234	$\lambda_{\beta_{F2}}$	0	0
ξ_R	3010214.074	2828143.974	λ_{β_G}	1	4
			λ_{β_H}	1	1
Bc_{B01}	2	11	λ_{β_J}	0	1
Bc_{B02}	17	17	$\lambda_{\beta_{K1}}$	0	1
Bc_{B03}	25	4	$\lambda_{\beta_{K2}}$	0	4
Bc_{B04}	9	23	$\lambda_{\beta_{K3}}$	0	4
Bc_{B05}	22	24	λ_{β_O}	2	3
Bc_{B06}	8	25	λ_{α_B}	3	3
Bc_{B07}	22	24	$\lambda_{\alpha_{F1}}$	1	0
Bc_{B08}	13	24	$\lambda_{\alpha_{F2}}$	0	2
Bc_{B09}	21	19	λ_{α_G}	0	0
Bc_{B10}	17	23	λ_{α_H}	0	0
Bc_{B11}	10	18	λ_{α_J}	1	0
Bc_{B12}	3	17	$\lambda_{\alpha_{K1}}$	0	1
Bc_{B13}	15	2	$\lambda_{\alpha_{K2}}$	0	0
Bc_{B14}	5	1	$\lambda_{\alpha_{K3}}$	0	0
Bc_{B15}	9	2	λ_{α_O}	0	0

Another way to decipher information from the optimisation is to search for clusters and rules in the data that could guide the decision maker towards solutions meeting various requirements (Ng et al., 2012). If we study input parameters plotted against running cost, there are more discoveries to be made. Step effects between parameter values regarding the objective indicate there is a rule to be found. Two examples are the λ_{α_B} parameter that should be equal to three to enable a solution to meet the running cost objective, as shown in Figure 4.12, and the λ_{β_H} parameter should be equal to one, illustrated in Figure 4.13. The proposed visual rule extraction technique is further explained in Chapter 7 (Section 7.6.2).

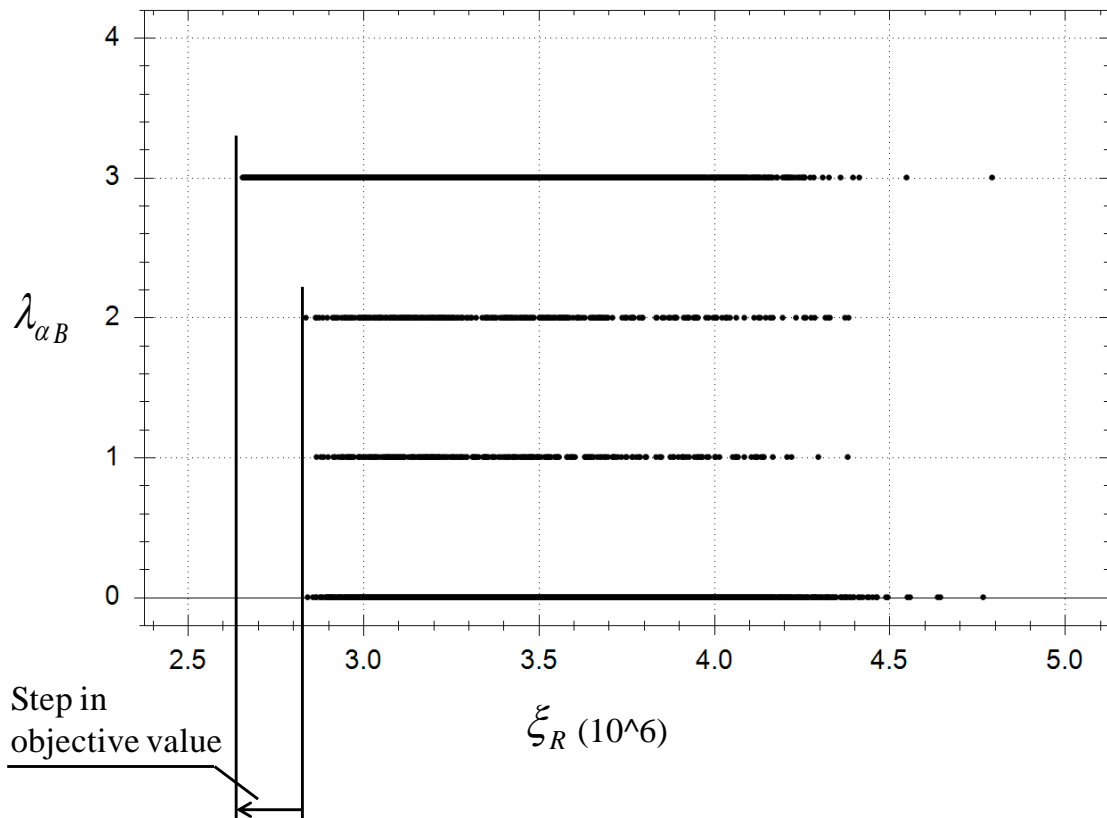


Figure 4.12. Step effect between parameter λ_{α_B} and the running cost objective.

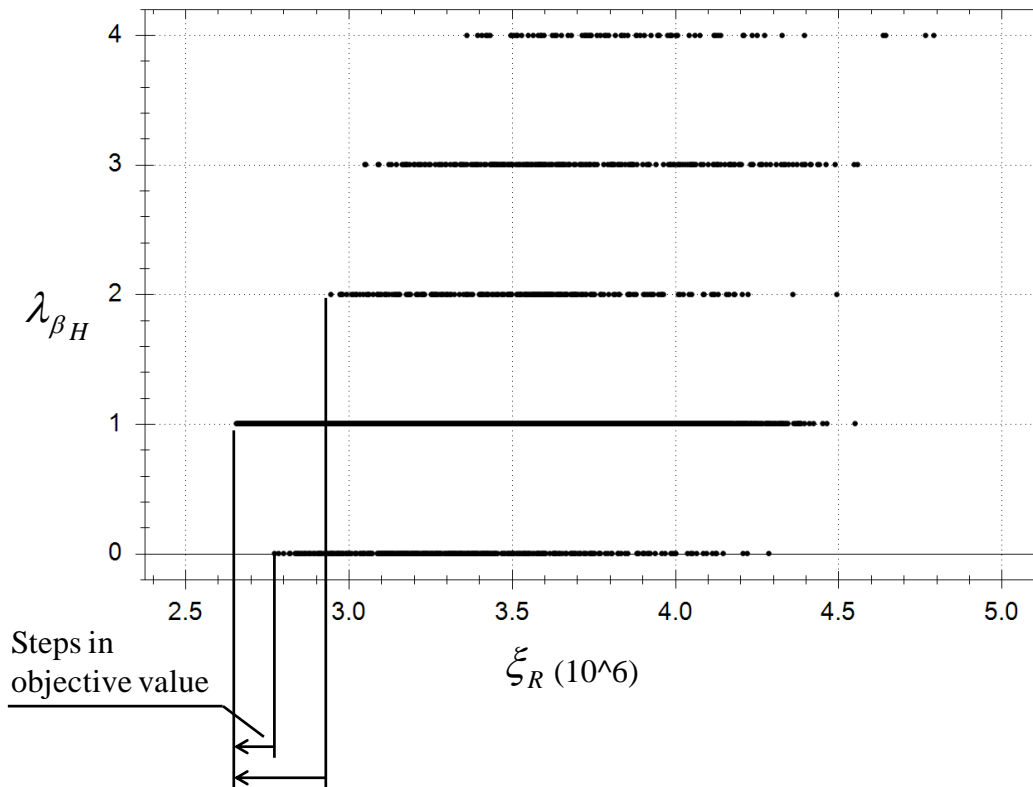


Figure 4.13. Step effect between parameter λ_{β_H} and the running cost objective.

These findings also correspond to the earlier discussed solutions A and B shown in Table 4.5. Knowing that $\lambda_{\alpha_B} = 3$ and $\lambda_{\beta_H} = 1$ are important rules and qualifiers that enable the system to operate within the objective requirements is essential information for the decision maker. After colour-coding the data according to the rules, we can learn more about how they affect the performance of the system, as shown in Figure 4.14.

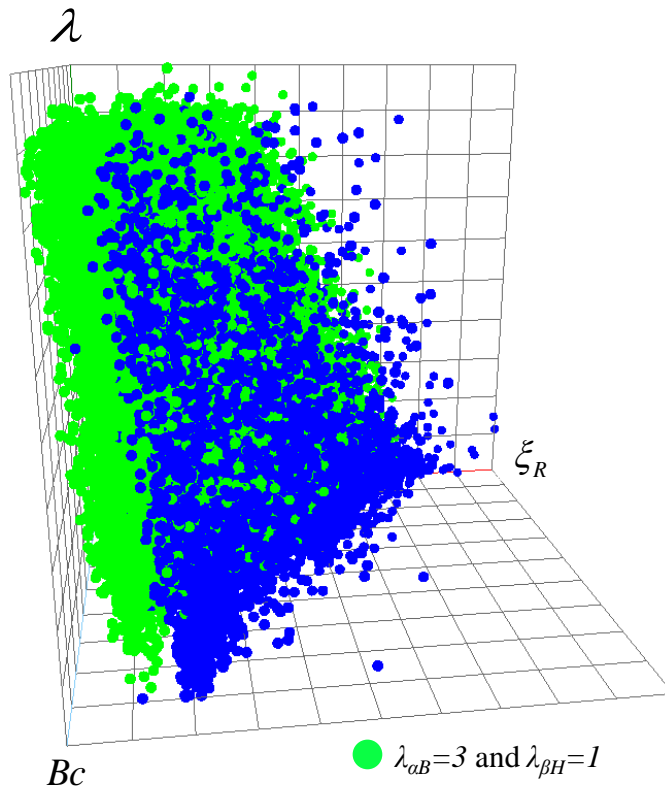


Figure 4.14. Complete data from optimisation with the discovered rules marked in green colour.

Actually, a very large portion of the Pareto front contains solutions fulfilling these rules and, in fact, the most beneficial solutions from a running cost saving in combination with relatively low lean buffer capacity all belong to this category. A decision maker prepared to invest should consider the parameters $\lambda_{\alpha B} = 3$ and $\lambda_{\beta H} = 1$ as the enablers of desirable trade-offs between the conflicting objectives.

4.6 Summary and key findings

A cost modelling method for integration with the framework proposed in Chapter 3 has been designed based on the literature review and industrial practices. In summary, an initial detailed cost calculation is the basis for the evaluation of differences induced by

changed input parameters, system properties or design options. The cost modelling method was integrated with the framework and tested on a hypothetical problem designed to replicate a real-world problem, in order to enable publication of detailed cost information. The value of post-optimality analysis is demonstrated through some examples of decision-making preparation using calculations of key performance indicators and the application of combined data mining and visualisation techniques.

Some findings and conclusions can be documented from the test of the proposed cost modelling method, as summarised below:

- One conclusion is that the modelling technique can be integrated with DES models and multi-objective optimisation as one of the components of the proposed framework.
- Valuable decision-making information can be found directly in the data from optimisation with cost objectives, while additional calculation and illustration of key performance indicators on optimised data can be used to show more about the consequences from various trade-off options.
- Deeper knowledge about the studied system can be found when visual data-mining (rule extraction) techniques are applied to discover rules for system setup or design.

Chapter 5.

Sustainability Modelling including testing

In this chapter, a sustainability modelling method for integration into the framework for manufacturing management and decision support using SMO, proposed in Chapter 3, is presented. The modelling technique is aligned with the cost modelling method proposed and tested in Chapter 4. An introduction to sustainability is followed by a proposal for a technique to model energy consumption, material consumption, and waste for connection to the framework proposed in Chapter 3. Aspects of cost modelling connections are considered and the modelling method is tested through integration with the decision-support framework. Finally, the findings are presented and summarised.

5.1 Introduction to Sustainability

Sustainability is emerging as an important aspect for companies worldwide to consider and already between 2004 and 2005 more than 50% of the companies in the G250 index, that is, the top 250 of the Fortune 500 list of companies with the highest annual turnover in the world, published corporate responsibility reports, including measurements of their sustainability performance (KPMG, 2005). In 2008 the corresponding figure of companies publishing corporate responsibility reports was 80% (KPMG, 2008). The International Federation of Accountants (IFA) has issued an international guidance document for Environmental Management Accounting (EMA) (International Federation of Accountants, 2005). According to IFA, some major potential applications for EMA are within the areas of cost-effective environmental regulation compliance, strategic positioning from the long-term competitiveness perspective and eco-efficiency initiatives that simultaneously reduce cost and environmental impact.

There are many definitions of sustainability due to its advocacy by a variety of groups. Overcash and Twomey (2011) have defined central features, or pillars, felt to be the most significant aspects in promoting industrial sustainability, namely, business excellence, innovation, human contribution, and environment. Glavic and Lukman (2007) have classified sustainability-oriented terms and use economy, society, and environment as a base. From this perspective, the complete framework, proposed in Chapter 3, could be considered to promote sustainability, especially when connected to cost models. Application of the framework might help a company towards business excellence, support innovation, involve human contribution, and include environmental aspects in decision-making. The models proposed in this Chapter should be seen as components complementing the framework from a sustainability perspective. In this context, the term sustainability is mainly used with regard to environmental aspects that may or may not be connected to monetary values and, if there is a connection to society, it is a secondary effect.

5.2 Sustainability Modelling

A modelling technique for sustainability factors has been developed, aligned with EMA, and derived from the modelling of financial and management accounting aspects applied on the optimisation of production systems in various phases spanning from conceptual development to the improvement of existing facilities, presented in Chapter 4. The proposed concept primarily focuses on common industrial environmental issues such as waste, material and energy consumption. Within EMA, these measures would be traced under the physical mass balance categories of non-product outputs and material inputs.

In order to facilitate the design of a complete framework for production systems decision support, one of the buildings blocks is to enable transparent connectivity between sustainability and the monetary domain. An endeavoured principle is to align

the mathematics of the sustainability modelling technique with other components in the framework.

The translation of sustainability measures into costs will initially relate to four EMA cost categories;

- Materials Costs of Product Outputs.
- Materials Costs of Non-Product Outputs.
- Waste and Emission Control Costs.
- Prevention and other Environmental Management Costs.

As a starting point for the modelling of electrical energy consumption, a first series of measurements has been conducted, with the help of specialists from Swerea SWECAST, on equipment within a facility for the production of automotive components. Various types of machines have been studied and a general example of a consumption pattern can be seen in Figure 5.1.

Based on the measurements, there is an indication that a total of three levels can be used to describe the average consumption patterns over time, of which two are during operation. The three levels are:

- High (working), based on the average consumption during machining.
- Low (not working), based on the average consumption during idling between machining cycles.
- Shut-down, based on the consumption when the equipment is turned off or in stand-by mode.

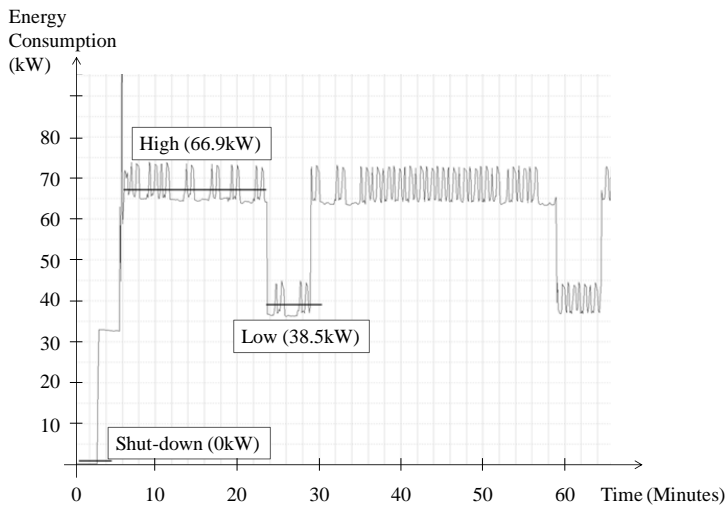


Figure 5.1. A general example of energy consumption pattern with low and high level (Swerea SWECAST).

An independent study, conducted in tandem by Skoogh et al., (2011), revealed similar results. They assigned their data into four machine states, namely, busy state, idle state, down state, and stand-by state. The differences are in how the idle and down states are broken into separate categories, something that could not be identified in the data from the Swerea SWECAST study. How energy consumption data can be aggregated might be dependent on the actual operations. Skoogh et al., (2011) also point out that their results are specific to the particular production system and the time of measurements for their study. Hence, it seems that the aggregation of energy consumption data for simulation model integration cannot be fully generalised and must be carried out according to the operations studied.

5.3 Sustainability model

The sustainability modelling will follow the main pattern of the cost modelling within the HSO framework, with an initial sustainability performance and delta sustainability reflecting the effect of various options and scenarios to be studied. Annual values are

used in order to correspond with forecasts, budget, and accounting values, in analogy with the cost modelling method proposed in Chapter 4.

In its most basic form, the sustainability model principle is described by (5.1):

$$\rho_A = \rho_I + \Delta\rho \quad (5.1)$$

where, ρ_A = Annual sustainability performance, ρ_I = Initial sustainability performance, $\Delta\rho$ = Delta sustainability performance.

Energy consumption modelled according to the sustainability modelling principle can be expressed as (5.2):

$$\varepsilon_A = \varepsilon_I + \Delta\varepsilon \quad (5.2)$$

where, ε_A = Annual energy consumption, ε_I = Initial energy consumption, $\Delta\varepsilon$ = Delta energy consumption.

Based on the three-level theory, the delta energy consumption expression can be expanded to include these parameters (5.3):

$$\Delta\varepsilon = \Delta\varepsilon_H + \Delta\varepsilon_L + \Delta\varepsilon_S \quad (5.3)$$

where, $\Delta\varepsilon_H$ = Delta energy consumption, high level, $\Delta\varepsilon_L$ = Delta energy consumption, low level or idle and $\Delta\varepsilon_S$ = Delta energy consumption, shut-down or stand-by.

By using an instance of the delta energy consumption expression for each consumption object applicable for analysis, the complete delta consumption can be modelled by a sum (5.4):

$$\Delta\varepsilon = \sum_{i=1}^m \Delta\varepsilon_i \quad (5.4)$$

where, m = The number of consumption objects.

Modelling of material consumption can be performed in the same fashion (5.5):

$$\mu_A = \mu_I + \Delta\mu \quad (5.5)$$

where, μ_A = Annual material consumption, μ_I = Initial material consumption and $\Delta\mu$ = delta material consumption.

By creating a sum of all deltas in material consumption, the complete production system material delta is described (5.6):

$$\Delta\mu = \sum_{j=1}^n \Delta\mu_j \quad (5.6)$$

Where, n = The number of consumption objects.

Waste can be modelled based, on the same principle, through the expression (5.7):

$$\omega_A = \omega_I + \Delta\omega \quad (5.7)$$

where, ω_A = Annual waste, ω_I = Initial waste and $\Delta\omega$ = delta waste.

The sum of waste deltas for a complete system can be expressed as (5.8):

$$\Delta\omega = \sum_{k=1}^o \Delta\omega_k \quad (5.8)$$

where, n = The number of objects with waste differences.

5.4 Sustainability Cost Model

Each of the sustainability components is likely to have specific units, not immediately comparable. Each sustainability component can be monitored in isolation from each other and be subject to optimisation as separate objectives. However, for complete integration into the framework, it is essential to calculate the cost impact of the sustainability components. The sustainability cost model is intended for integration with the cost model proposed in Chapter 4. The transference of the sustainability parameters

into the financial domain and cost is conducted by multiplication with a cost factor corresponding to the unit of the specific sustainability component.

The principal expressions for transferring each sustainability component to cost are then (5.9) to (5.11):

$$\Delta\xi_E = \Delta\varepsilon \cdot \xi_{FE} \quad (5.9)$$

$$\Delta\xi_M = \Delta\mu \cdot \xi_{FM} \quad (5.10)$$

$$\Delta\xi_W = \Delta\omega \cdot \xi_{FW} \quad (5.11)$$

where, $\Delta\xi_E$ = delta energy cost, ξ_{FE} = energy cost factor, $\Delta\xi_M$ = delta material cost, ξ_{FM} = material cost factor, $\Delta\xi_W$ = delta waste cost and ξ_{FW} = waste cost factor.

Since there might be various cost factors for each component within a production system, it will occasionally be necessary to have multiple parameters in a model that can be described through the following expression including a custom sustainability cost component, in order to enable tailored applications (5.12):

$$\Delta\xi_S = \sum_{i=1}^m \Delta\xi_{Ei} + \sum_{j=1}^n \Delta\xi_{Mj} + \sum_{k=1}^o \Delta\xi_{Wk} + \Delta\xi_{SC} \quad (5.12)$$

where, $\Delta\xi_S$ = Sustainability delta cost and $\Delta\xi_{SC}$ = Custom sustainability cost component.

Following is the complete sustainability cost expression in its simplified form:

$$\Delta\xi_S = \Delta\xi_E + \Delta\xi_M + \Delta\xi_W + \Delta\xi_{SC}$$

5.5 Sustainability investments

Investments due to sustainability issues are added to the cost model (see Chapter 4) by including the sum of sustainability related investments for any given scenario, using the following expression:

$$\lambda_s = \sum_{i=1}^m \lambda_{s_i} \quad (5.13)$$

where, λ_s = Sustainability investment and m = the number of investment options in the simulation model.

5.6 Test

The main purpose of this test is to make a first proof of concept for the sustainability components in the SMO framework.

A plant that produces components for the automotive industry is planning to expand its production by introducing a completely new line for a new range of products. Due to the strategy of the company, sustainability objectives, and increasing electrical energy costs, there is a demand for the evaluation of the potential effect from increased maintenance, in order to reduce energy consumption. Could SMO with integration of sustainability parameters be of assistance when conducting such evaluations?

A conceptual-phase simulation model of the line was built with input and data from existing production facilities and equipment suppliers. Electrical energy consumption patterns for relevant machine types were logged in an existing line and divided into the three categories of running, idle, and stand by. The energy consumption figures were updated to reflect the behaviour of the new equipment and coolant supply pump stations.

The required operation time of the line is dependent on the actual capacity or the throughput from the line. An estimation of the required maintenance cost to achieve a

certain level of availability was made by the expressions, based on information from a component manufacturer (5.15):

$$\begin{aligned}\xi_{m_i} &= (\beta OP_i - 70)^3 \\ 85 &\leq \beta OP_i \leq 99 \\ \xi_m &= \sum_{i=1}^m \xi_{m_i}\end{aligned}\quad (5.15)$$

where, ξ_{m_i} = Delta maintenance cost for equipment i , βOP_i = Availability of equipment i and ξ_m = Incremental maintenance cost for the complete system.

The optimisation objectives were (5.16):

$$\begin{aligned}\xi_m & \text{ (min)} \\ \xi_E & \text{ (min)}\end{aligned}\quad (5.16)$$

The result from the optimisation, plotted in the form of a Pareto frontier, can be seen in Figure 5.2.

The Pareto frontier resulting from the optimisation illustrates that energy cost can be reduced by increased maintenance and increased maintenance cost. Up to a certain level, the reduced energy cost is greater than the added maintenance cost. Above that point, the energy saving by itself is not a motivating factor for increased maintenance. There might, however, be other savings, resulting from the increased maintenance, which are related to such benefits as increased throughput or improved quality. However, the purpose of this study was achieved in testing and demonstrating the integration of sustainability models into the framework, proposed in Chapter 3, with connection to the cost models introduced in Chapter 4.

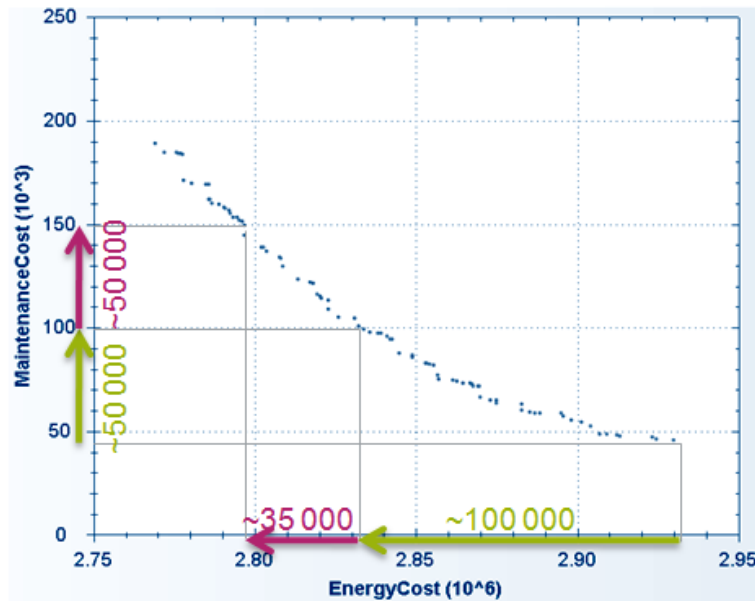


Figure 5.2. Pareto frontier from optimisation showing maintenance cost vs. energy cost.

5.7 Summary and key findings

A sustainability modelling technique was proposed in alignment with the cost modelling method proposed in Chapter 4 and for the purpose of integration with the decision-support framework proposed in Chapter 3. The sustainability modelling is based on an initial state which is designed to evaluate differences introduced by changes to input parameters or conceptual choices. Energy consumption is aggregated into three levels connected to equipment status monitored in the connected simulation model. The modelling technique is successfully tested through integration with the decision-support framework and the main conclusion is that such a modelling technique can enhance the decision-making potential of the complete method.

Some findings and conclusions can be documented from the test of the proposed sustainability modelling method, as summarised below:

- One finding is that it seems to be possible to save energy, to some extent, without adding cost to the system. However, there is a level above which further maintenance costs cannot be motivated by energy savings alone.
- How energy consumption data can be aggregated for integration with simulation models seems to depend on the nature of the operations and such a task cannot be fully generalised. However, there are patterns in data from independent sources that enable categorising for simulation model integration.
- The main conclusion from this study is that the sustainability modelling has potential for integration in the decision-support framework, enhancing the decision-support potential of the complete method.

Chapter 6.

Bottleneck detection including testing

One of the drawbacks with current industrial methods, touched upon in Chapter 1 and further identified in Chapter 2, is related to the identification of constraints and bottlenecks in production systems. Several methods for production system improvement require the bottleneck to be known, in order to produce the desired effect. Still, most of the bottleneck detection methods available are quite rudimentary and not always applicable on complicated systems. Another issue with current methods is the difficulty in predicting sequential constraints or bottlenecks, in order of importance. In this Chapter, a new method for the detection of bottlenecks and production systems constraints is proposed, building upon the framework introduced in Chapter 3. The new method is tested against the established shifting bottleneck detection technique and the findings are presented at the conclusion of the chapter.

6.1 Introduction

The automotive industry constantly needs to explore strategies that will accelerate the efficiency of the industrial system, in a severely competitive situation, that requires more precise decision-support information. A very important issue within manufacturing management and production system development is to identify the limiting factors of production systems, in order to target initiatives for the improvement of system performance. Excellence in manufacturing is often a result of a combination of successive incremental improvements and investment in technology or equipment (Sim 2001). In order to improve throughput, operational expense or inventory in production systems, the ToC suggests improving the constraint of the system (Goldratt, 1984). According to ToC, the operational expense is all the money the system spends in

order to turn inventory into throughput. When the goal of the operation has been defined, there are a number of steps to follow, according to ToC. The first is to identify the constraint, the second is to exploit it, all other processes should then be subordinated, thereafter, the constraint should be evaluated and, finally, if the constraint has moved, return to step one. This process requires a method or a technique with the capability to identify the constraints within a specific production system. It is also imperative to obtain enough information about the situation to identify the right type of action to remove the constraint. One such goal, with regard to production lines, is to increase throughput limited by bottlenecks in the system. Examples of definitions of bottlenecks include the machine whose performance affects the overall system throughput in the strongest manner or the machine most sensitive to the overall system performance (Kuo et al., 1996, Li, 2009 and Roser et al., 2003). It follows that the improvement of such a machine results in significantly increased throughput from the system compared to the improvement of a non-bottleneck machine. The magnitude of a bottleneck can be defined as the magnitude of the machine's throughput effect related to the system's throughput (Roser et al., 2003). There are several methods of identifying bottlenecks in production lines, such as Simple bottleneck (Grosfeld-Nir, 1995), Multiple Bottleneck (Aneja and Punnen 1999), and the shifting bottleneck detection technique (Roser et al., 2002). Various methods for detecting momentary and dominant (average) bottlenecks, partially listed (Sengupta et al., 2008), include the shifting bottleneck detection technique, utilisation of machines, up-stream queue, blocking and starving probabilities, a graph-theoretic approach, and a proposal for a new method based on inter-departure time and failure cycle data. Many of the known methods can be categorised into analytical or simulation-based methods (Li, 2009). The analytical methods have many constraints restricting them to long-term, steady state bottleneck detection when used on complex systems, partly due to the assumption of exponentially distributed performance metrics. The simulation-based methods with the ability to pinpoint bottlenecks in complex production lines might require a long development time and could have issues with the possible misinterpretation of the simulation results limiting its wide application (Li, 2009). Even so, it is widely accepted that the only

general purpose and generally applicable modelling tool for truly complex production systems is simulation (Fu et al., 2000), particularly, the most promising tool to support decision-making in production systems design and analysis, discrete-event simulation (DES). There are also combinations of methods when analytical approaches are used with simulation models and DoE for verification (Faget et al., 2005). However, there are still some other drawbacks with the current methods. Even if the overall constraint of a system can be identified down to a specific work cell, operation, or station in the system, the exact nature of the constraint is still unknown. A deep implementation of the shifting bottleneck technique could partly provide this type of information as well as an indication of what the problems might be, but this is often not detailed enough to enable the right decision to be made about what action to take. In some cases this could be a serious disadvantage, since local improvement of the wrong parameter might actually decrease the performance of the whole system (Ignizio, 2009). Another issue is how to interpret the results from previous methods when applied on complicated production systems with buffers, parallel and serial flows, feedback loops, operational logic, rework, and variant specific operations. It is likely that the more complex the system, the more complex it is finding the right combination of improvement actions to enhance the performance of the system, especially with a limited budget. The framework, proposed in Chapter 3, building upon SMO and innovization (Deb and Srinivasan, 2006) meaning innovation through optimization, is a platform that enables the development of new analysis tools and decision-support methods for application on production systems. The framework amalgamates the strengths of simulation with specialised optimisation modelling techniques, MOO, using various algorithms, extensive post-optimality processing and analysis methods, as well as state of the art visualisation options, in order to facilitate decision-making within manufacturing enterprises. In order to solve some of the issues with current methods for bottleneck detection, a new approach is submitted, based on the framework proposed in Chapter 3. The basic theory from ToC, which essentially states that a chain is no stronger than its weakest link, is still valid for this approach, although it does not necessarily have to be a station or a machine that is considered a constraint. Instead, the limitation in system

performance could be due to a specific property or parameter in one of the system's links.

6.2 The SCORE method

In an attempt to address some of the issues with current bottleneck detection practices, the Simulation-based COnstraint REmoval (SCORE) method was developed. Its basic principle is to optimise the system's throughput and find the constraints that need to be removed, in order to improve the systems performance. This approach has some similarities to DoE for bottleneck verification (Faget et al., 2005). The essential constraints considered by the first version of the method are work cell cycle time, work cell availability, and work cell MDT. There is an opportunity to include other possible constraints as well, together with buffer capacity.

The SCORE-method is based on finding the most beneficial improvements for a production line through the use of simulation-based MOO. Through setting improved values for a number of local system parameters, such as station cycle time, station availability and MDT, while minimising the number of such changes and simultaneously maximising throughput of the system, solutions with the most beneficial throughput improvement given the fewest number of system changes will be found. The constraining parameter can be found by noting the setting with the highest frequency in the optimisation results, especially when studying solutions close to the Pareto front or on the Pareto front. According to ToC, there will be one constraint slowing down the complete system. The parameter with the highest frequency in the optimisation results is most likely the constraint of the system. Solutions with the parameter of the highest frequency set to improved state can be regarded as an improved version of the system. It is then likely that the parameter with the second highest frequency is the secondary constraint, and so on. Hence, the order of several bottlenecks in the system can be established.

The foundation of the method is the combination of a validated discrete event model of the production system with input parameters controlled using EMO. Constraint removal is introduced by discrete two-level parameters that can either be set to the systems original value or to a value representing a removed constraint. Data is generated by an optimisation of the system, with the objectives of minimising the number of changes (removed constraints) and at the same time maximising the throughput performance. The basic optimisation problem can be summarised by the formulas 6.1 and 6.2.

$$\min(\sum_{i=1}^m \hat{A}_i + \sum_{i=1}^m \hat{C}_i + \sum_{i=1}^m \hat{D}_i) \quad (6.1)$$

where:

$\hat{A}_i = 0$, if availability of workstation i is not improved and remains to be β_i , or; $\hat{A}_i = 1$, if availability of workstation i is improved (increased) from β_i to $\hat{\beta}_i$.

$\hat{C}_i = 0$, if cycle time of workstation i is not improved and remains to be α_i , or; $\hat{C}_i = 1$, if cycle time of workstation i is reduced from α_i to $\hat{\alpha}_i$.

Similarly, $\hat{D}_i = 0$, if the mean down time of workstation i is not improved and remains to be γ_i , or; $\hat{D}_i = 1$, if mean down time of workstation i is improved (reduced) from γ_i to $\hat{\gamma}_i$.

$$\max(\varphi) \quad (6.2)$$

where: φ = Production system throughput.

It is also possible to introduce other objectives, besides the number of changes and throughput, into the optimisation, such as factory cycle time or work in process. Post-optimality analysis, according to the concept of innovization (Deb and Srinivasan, 2006), is conducted through a frequency analysis within non-dominated (Deb, 2001) solutions or solutions belonging to rank 1 to n from the optimisation. The frequency of

occurrence for a specific constraint removal will indicate the level of importance from a constraint perspective. A similar method has been proposed for a multi-objective optimisation sports team selection approach (Ahmed et al., 2011). The findings are presented to the user by plotting the frequency or occurrence percentage within the chosen data set, in a Pareto chart. If we want to improve the performance of the line according to ToC, the limitations in the production flow should be removed in order of importance and the optimisation should be able to find such solutions when the number of changes to the system are minimised. Since the frequency analysis is performed on solutions at the Pareto front or very close to the Pareto front, the most influential constraints will occur at a higher frequency than the less important constraints. Hence, since various types of constraints are included in the optimisation, it will be possible to not only discover where to improve, but also which type of improvement is required to enhance the performance of the whole system.

However, there are some disadvantages with the proposed method. First, it will require quite a lot of computing power, in order to solve problems in a reasonable amount of time. Second, a simulation model of the production system is required. Third, an implementation of the SCORE-specific parameters into the simulation model and integration with the controlling algorithm must be conducted. With regard to the computation requirements, the development in parallel processing combined with the use of clustered computers can provide extensive power at a reasonable cost, reducing the analysis time sufficiently. The cost issue can be further reduced by utilising cloud computing and opportunities for several users to share computational resources. In recent years, the development of methods for faster simulation modelling at a fair aggregation level (Ng, et al., 2007) have significantly reduced the modelling efforts needed to produce an accurate virtual representation of a production system. By automating the parameter and algorithm integration, a simulation model can be prepared for the SCORE-analysis with the push of a button.

The shifting bottleneck detection technique (Roser et al., 2002) is used in comparison to the SCORE method and can be summarised as follows and as shown in Figure 6.1.

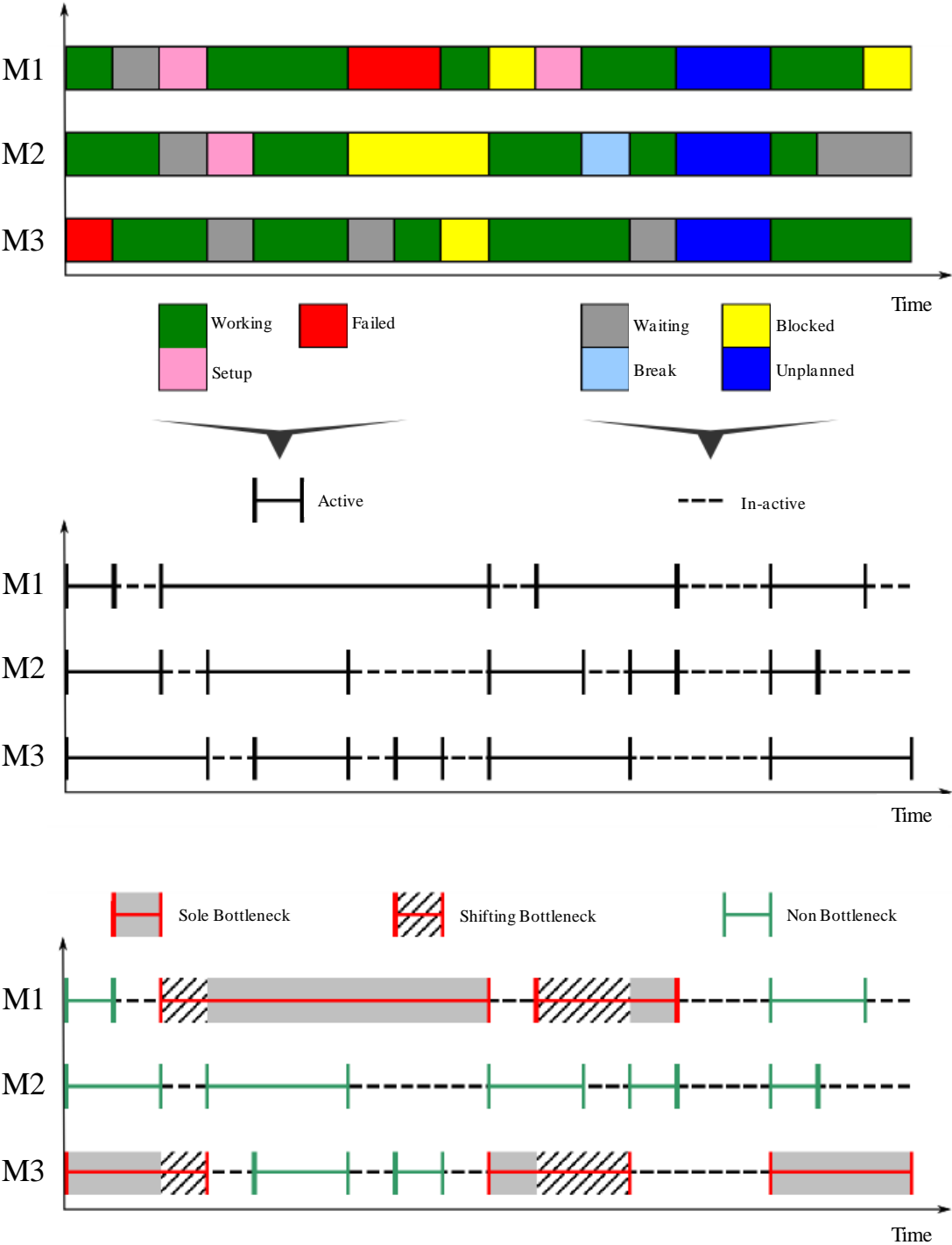


Figure 6.1. The shifting bottleneck principle (from the FACTS Analyser help file).

During production, the machines in a production line alter state over time. The different states of working, failed, setup, waiting, and blocked are logged together with information about breaks and unplanned activities, in order to perform the shifting bottleneck analysis. The different states are grouped into active and in-active periods, where the states of working, failed, and setup are considered active. The momentary bottleneck is the machine with the longest active period. If there is an overlap between two consecutive bottlenecks, the overlap period is marked as a shifting bottleneck period and both bottlenecks are considered momentary bottlenecks during the shifting period. When just one machine is a bottleneck, it is referred to as the sole bottleneck. Presentation of the results from a shifting bottleneck analysis is achieved by plotting the percentages of the total time that each machine has been a sole bottleneck and shifting bottleneck.

6.3 Simulation model integration and testing

One way of validating the method is by application on basic production system examples with obvious constraints prepared in simulation models. A DES model of a line with five work stations, M_1 to M_5 , without inter-station buffers, Figure 6.2, was prepared for control by a genetic algorithm with two level parameters for work cell cycle time, work cell availability and work cell MDT, considered to be potential constraints. In this case, a workstation is a production resource that could include one machine and/or one worker. The mean downtime parameter is not be used in this case, due to the lack of buffers in the simple line example. However, the functionality was implemented for future experiments on more complex models. The first level, 0, represents the original value and the second level, 1, represents a removed constraint. The principle for integration of the parameters is shown in Table 6.1.

Table 6.1. SCORE test model parameters.

Parameter	Description	M_1	M_2	M_{\dots}	M_n
α	Work station cycle time	α_1	α_2	α_{\dots}	α_n
$\hat{\alpha}$	Work station cycle time, constraint removed	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\alpha}_{\dots}$	$\hat{\alpha}_n$
β	Work station availability	β_1	β_2	β_{\dots}	β_n
$\hat{\beta}$	Work station availability, constraint removed	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_{\dots}$	$\hat{\beta}_n$
γ	Work station MDT	γ_1	γ_2	γ_{\dots}	γ_n
$\hat{\gamma}$	Work station MDT, constraint removed	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_{\dots}$	$\hat{\gamma}_n$

The specific case studies were carried out with the constraint removal levels set according to formula (6.3) to (6.5):

$$\hat{\alpha}_i = \alpha_i \cdot 0.7 \text{ (s)} \quad (6.3)$$

$$\hat{\beta}_i = 99 \quad (\%) \quad (6.4)$$

$$\hat{\gamma}_i = 1 \quad (\text{minute}) \quad (6.5)$$

The purpose of the first case study was to explore the method's capability to detect a work cell cycle time constraint in one of the operations of our line example. All work cell cycle times in the line were set to 30 s., except the cycle time in M_2 that was set to 40 s., all availabilities were set to 90% and all MDTs to 10 minutes, as shown in Table 6.2.

Table 6.2. Original parameter values and constraint removal values in the cycle time constraint detection test.

Parameter	Description	M ₁	M ₂	M ₃	M ₄	M ₅
α	Work station cycle time	30	40	30	30	30
$\hat{\alpha}$	Work station cycle time, constraint removed	21	28	21	21	21
β	Work station availability	90	90	90	90	90
$\hat{\beta}$	Work station availability, constraint removed	99	99	99	99	99
γ	Work station MDT	10	10	10	10	10
$\hat{\gamma}$	Work station MDT, constraint removed	1	1	1	1	1

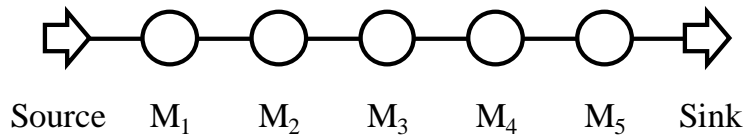


Figure 6.2. Simulation model for SCORE-analysis testing.

The simulation model was optimised by running 1000 iterations with 5 replications controlled by the NSGA-II evolutionary algorithm (Deb, 2001). The objectives were to minimise the number of changes (constraint removals) and to maximise the throughput. The non-dominated solutions from the resulting data set were then analysed with regard to constraint removal frequency for each operation. The relative frequencies of occurrence for the constraint removal parameters are plotted in a Pareto chart shown in Figure 6.3.

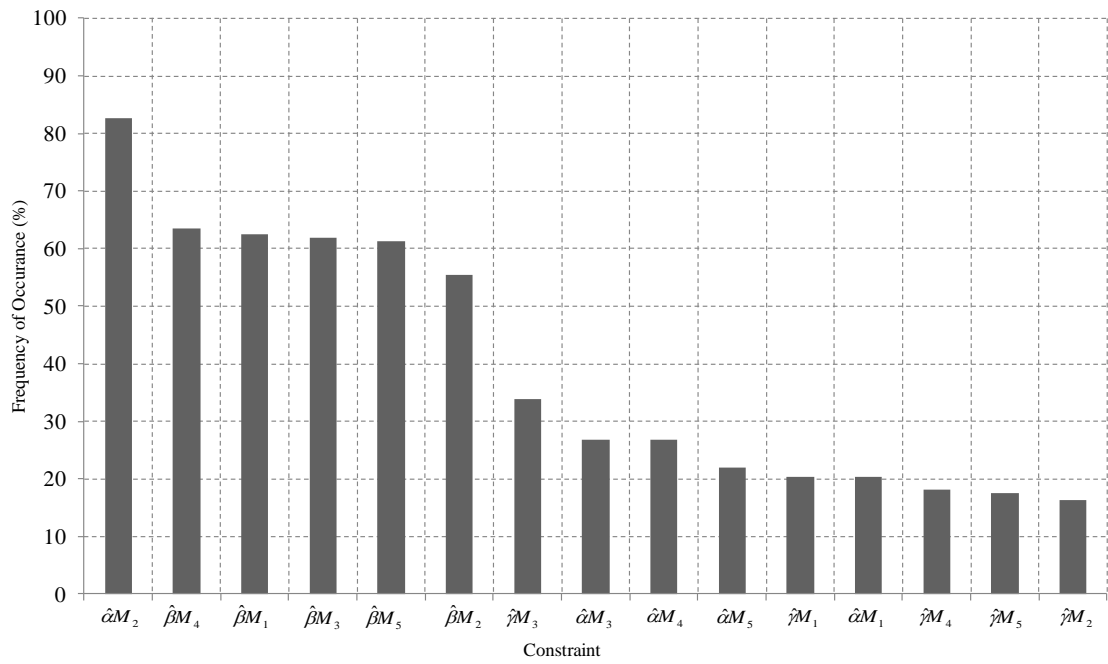


Figure 6.3. SCORE-analysis results from test on cycle time constraint.

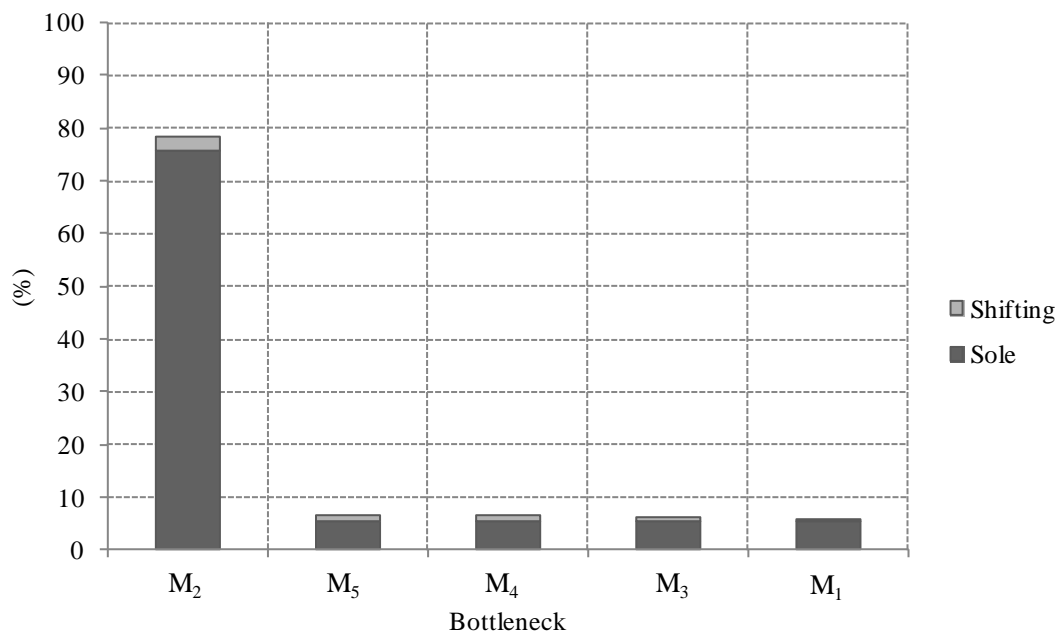


Figure 6.4. Shifting bottleneck analysis detecting M_2 with the cycle time constraint.

First, according to the Pareto chart, the most important parameter that needs to be changed is the cycle time in M_2 which is the constraint of the system. Second, it is likely that the improvement of availability in any of the operations could improve the performance of the system.

The Shifting bottleneck method was run in parallel for the purpose of verification. It also detects M_2 as the bottleneck of the system, but reveals no information on the type of constraint, as indicated in Figure 6.4.

What about trying to detect a pronounced availability constraint in one of the operations? Another experiment was set up in which all availability figures were set to 90%, except in M_3 where it was set to 80% with all cycle times at 30 seconds, according to Table 6.3. Another optimisation was run in the same way as in the first experiment and a frequency analysis was performed. The resulting Pareto chart is shown in Figure 6.5.

Table 6.3. Original parameter values and constraint removal values in the availability constraint detection test.

Parameter	Description	M_1	M_2	M_3	M_4	M_5
α	Work station cycle time	30	30	30	30	30
$\hat{\alpha}$	Work station cycle time, constraint removed	21	21	21	21	21
β	Work station availability	90	90	80	90	90
$\hat{\beta}$	Work station availability, constraint removed	99	99	99	99	99
γ	Work station MDT	10	10	10	10	10
$\hat{\gamma}$	Work station MDT, constraint removed	1	1	1	1	1

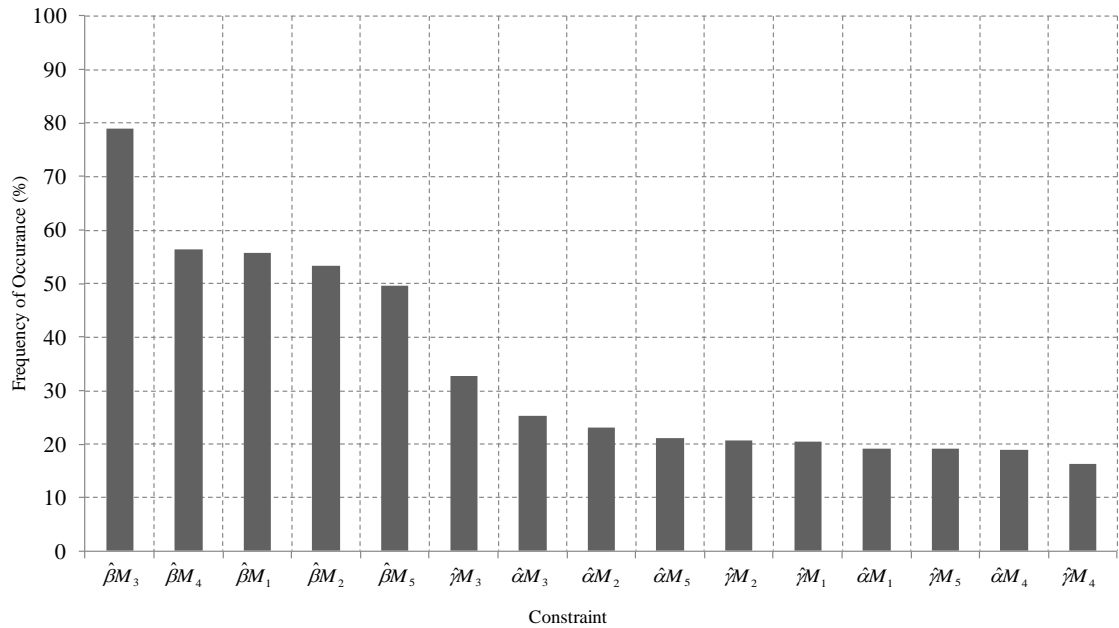


Figure 6.5. CORE-analysis results from test on availability constraint

In this case, the most important parameter to improve is the availability in M_3 , the constraint of the system.

The shifting bottleneck method was also used as reference for this experiment and M_3 was detected as the bottleneck of the system, shown in Figure 6.6.

A third experiment was conducted, combining the two types of constraints in the same model, as shown in Table 6.4. In Figure 6.7, the resulting Pareto chart clearly illustrates how the method pinpoints the two major constraints in M_2 and M_3 . The most beneficial improvement to the system is to reduce the cycle time in M_2 . The next parameter to prioritise would be the availability in M_3 .

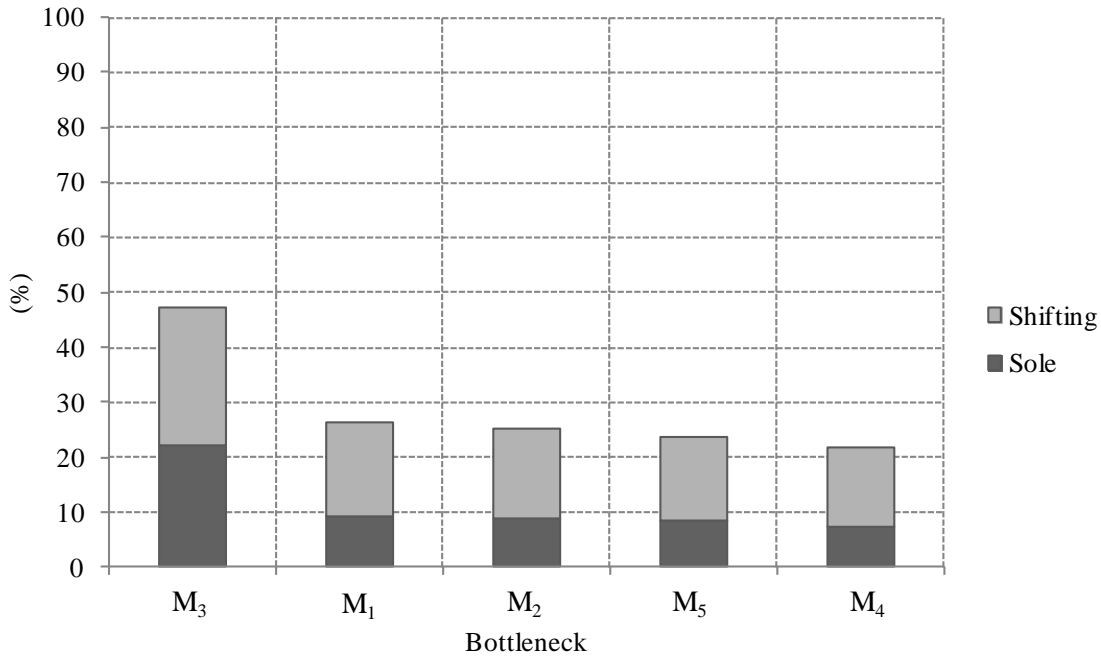


Figure 6.6. Shifting bottleneck detecting M_3 with the availability constraint.

Table 6.4. Original parameter values and constraint removal values in the combined cycle time and availability constraint detection test.

Parameter	Description	M ₁	M ₂	M ₃	M ₄	M ₅
α	Work station cycle time	30	40	30	30	30
$\hat{\alpha}$	Work station cycle time, constraint removed	21	28	21	21	21
β	Work station availability	90	90	80	90	90
$\hat{\beta}$	Work station availability, constraint removed	99	99	99	99	99
γ	Work station MDT	10	10	10	10	10
$\hat{\gamma}$	Work station MDT, constraint removed	1	1	1	1	1

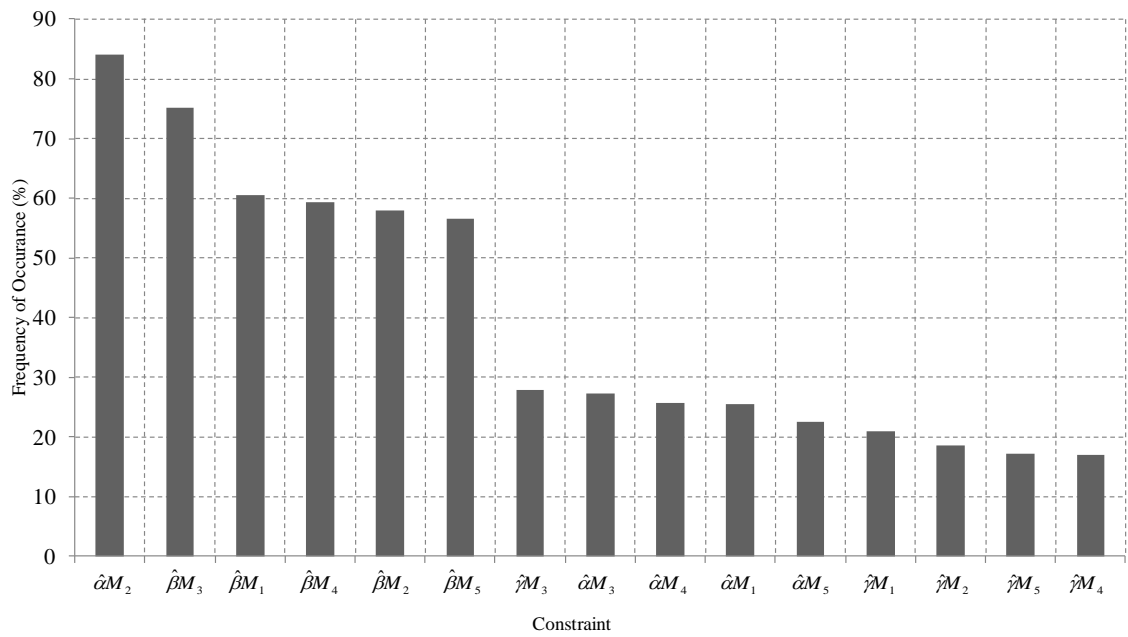


Figure 6.7. CORE-analysis results from test on the combined cycle time and availability constraints.

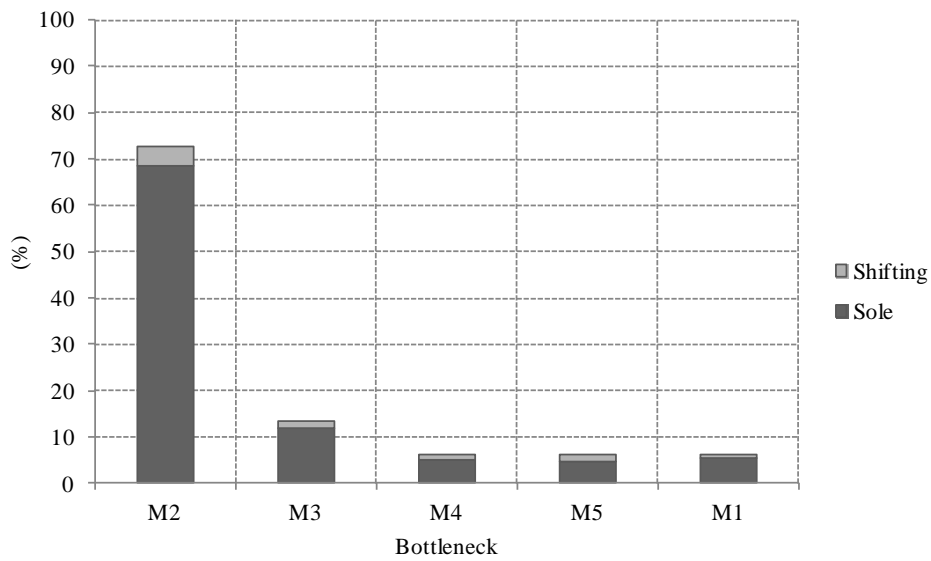


Figure 8. The shifting bottleneck reference test for combined cycle time and availability constraints

The last part of the generic case study was done on the same simple line with several mixed issues spread over the five operations, according to table 6.5.

Table 6.5. Several mixed issues test.

Parameter	Description	M ₁	M ₂	M ₃	M ₄	M ₅
α	Work station cycle time	32	35	30	33	31
$\hat{\alpha}$	Work station cycle time, constraint removed	22.4	24.5	21.0	23.1	21.7
β	Work station availability	95	92	86	94	90
$\hat{\beta}$	Work station availability, constraint removed	99	99	99	99	99
γ	Work station MDT	10	10	10	10	10
$\hat{\gamma}$	Work station MDT, constraint removed	1	1	1	1	1

The results from the shifting bottleneck analysis pinpoints M₂ as the bottleneck, followed by M₃, as shown in Figure 6.10. Interestingly, the SCORE method illustrates another result, indicating the availability in M₃ as the main constraint, followed by the availability in M₅, as shown in Figure 6.9.

In order to compare the two methods, each method's order of improvements was simulated, step by step. Each scenario was replicated 5 times with a simulation horizon of 6 days, including one day for warm-up. The cycle times were improved to 30 seconds and the availabilities to 99%. The performances of the two methods were compared for an equal number of improvements. In the case of the shifting bottleneck method, both the cycle time and the availability were improved, together resulting in steps of two improvements. The result, shown in Figure 6.11, reveals the potential released by the SCORE method, showing a more than 7% higher performance advantage for the first six steps of improvement and an advantage all the way until all the improvements have

been implemented. More detailed information on the simulation results is found in Table 6.6.

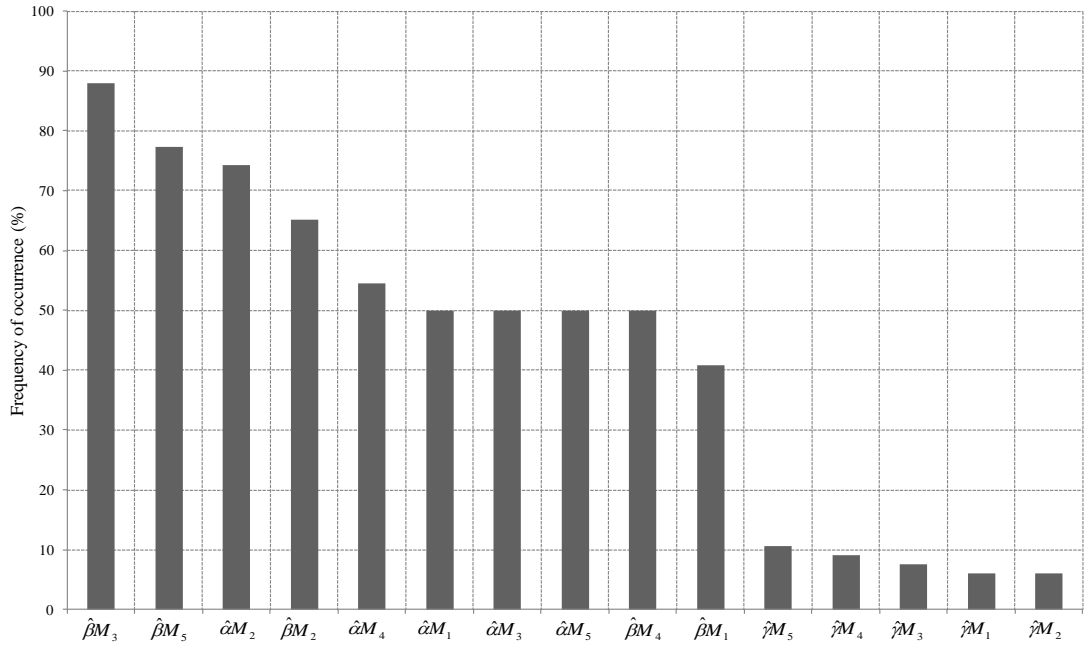


Figure 6.9. SCORE results for the mixed issues test.

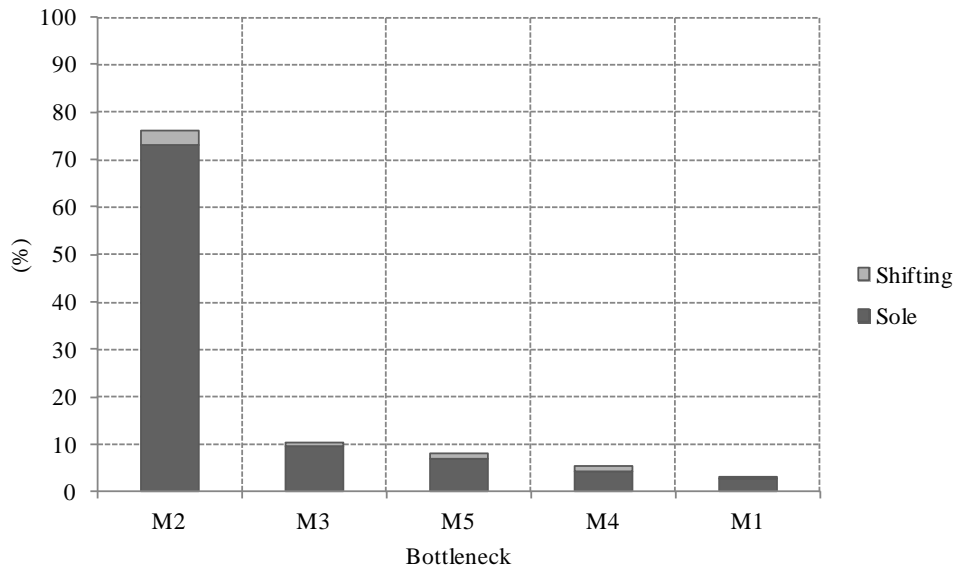


Figure 6.10. The shifting bottleneck reference test for the mixed issues constraints detection test.

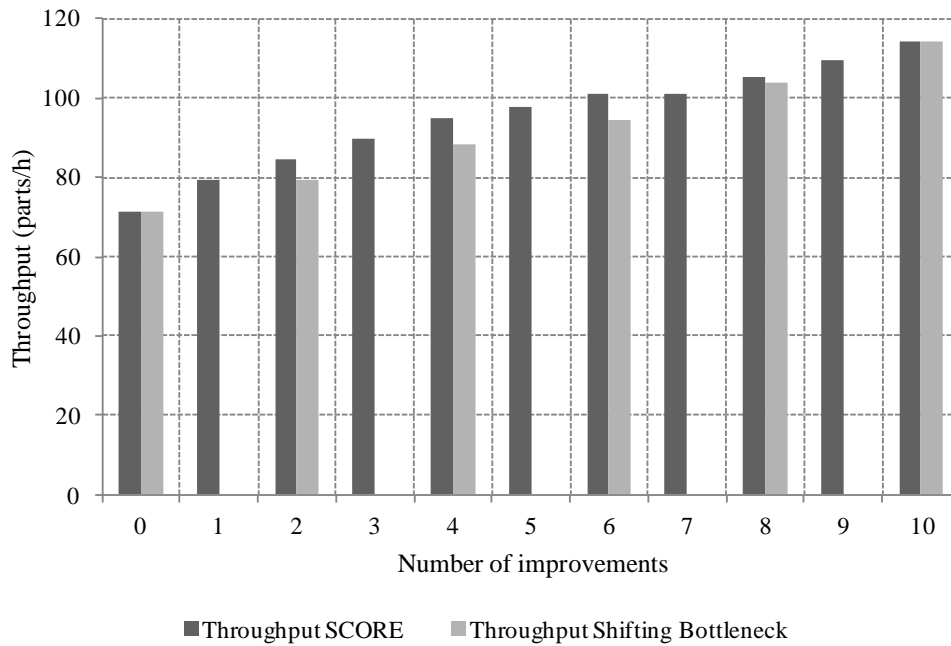


Figure 6.11. Simulation results comparing improvements based on SCORE and shifting bottleneck.

Table 6.6. Simulation results comparing improvements based on SCORE and shifting bottleneck.

No of Changes	Throughput SCORE	Throughput Shifting Bottleneck	SCORE advantage
0	71.18	71.18	0.00%
1	79.36		
2	84.72	79.15	7.04%
3	89.55		
4	94.94	88.38	7.42%
5	97.89		
6	101.16	94.27	7.31%
7	101.16		
8	105.35	103.77	1.52%
9	109.49		
10	114.29	114.29	0.00%

One could argue that it would be possible to conduct a deeper analysis based on the shifting bottleneck technique and find the most beneficial improvement for each machine, selecting cycle time and availability improvements in the correct order. In order to illustrate the effect of such prioritisations, two improvement strategies were simulated and studied, using the best case and the worst case selections. This would require more knowledge about the system than the shifting bottleneck method has revealed, but might still be relevant from a perspective of available consequences related to decision-making. The results from this study are shown in Figure 6.12 and Table 6.7.

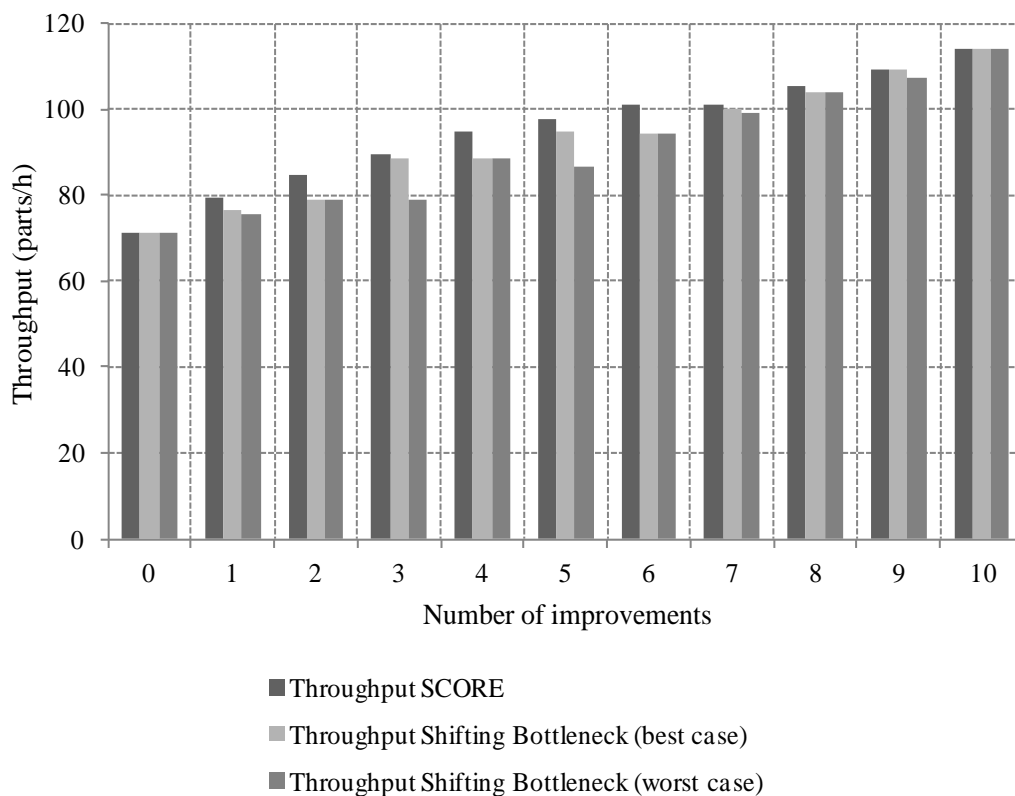


Figure 6.12. SCORE compared to the best case and the worst case improvement strategies based on shifting bottleneck detection analysis.

Table 6.7. SCORE-based improvements compared to best and worst case improvements based on shifting bottleneck detection analysis.

No of Changes	Throughput SCORE	Throughput Shifting Bottleneck (best case)	Throughput Shifting Bottleneck (worst case)
0	71,18	71,18	71,18
1	79,36	76,56	75,58
2	84,72	79,15	79,15
3	89,55	88,38	79,15
4	94,94	88,38	88,38
5	97,89	94,94	86,76
6	101,16	94,27	94,27
7	101,16	100,3	99,09
8	105,35	103,77	103,77
9	109,49	109,49	107,35
10	114,29	114,29	114,29

As shown in Figure 6.12 and Table 6.7, the prediction performance for SCORE is better through the whole series of experiments until all improvements have been implemented.

Another argument for a comparison such as this could be that the shifting bottleneck detection technique (to an extent) and other conventional bottleneck detection methods are not designed to find several levels of bottlenecks in a single analysis run. However, the overlapping (shifting) functionality of the shifting bottleneck technique could allow some conclusions to be drawn about secondary bottlenecks. With other analysis methods, the bottleneck would have to be improved before the search for the next bottleneck could begin. On the other hand, the SCORE method has the built-in ability to perform detection of the primary, secondary, and lower levels of bottlenecks ranked in order from the most beneficial improvement and improvement strategy, in one optimisation run.

The advantages of using the SCORE method on more complicated real life problems could be quite considerable, in view of the potential shown from the simple line in this

generic case study. The results also indicate that we might need to re-think how we perceive bottlenecks. Just finding an operation or station to improve is not enough. We need to consider what property or parameter to improve in the system, in order to remove the real constraint with a minimum of effort and resources. In Chapter 7 the method will be applied on an industrial problem and connected to the cost model introduced in Chapter 4. The opportunities of finding the required levels of improvement are also explored in Chapter 7.

6.4 Summary and key findings

A new method for bottleneck detection or, rather, constraints detection was derived as a special application of the decision-support framework proposed in Chapter 3. Through optimising where to remove constraints, in order to improve throughput, followed by a frequency analysis on the resulting data, the constraints of a production system can be identified and ranked in order of importance. The order in which the most beneficial improvements should be made can be predicted in a single optimisation and analysis run. This will allow the improvement of production systems with higher performance development than the shifting bottleneck technique. A new perspective on bottlenecks, which takes not just where to improve into consideration, but also what to improve and in which order, could be an advantage. In Chapter 7, the new method is applied on a real-world industrial problem and the opportunities of finding the required levels of improvement are explored. In conclusion, the proposed method has the potential to substantially enhance the prerequisites for decision-making within manufacturing management, production systems development and improvement.

The most important findings can be summarised as below:

- The SCORE method has the ability to perform detection of the primary, secondary, and lower levels of bottlenecks, ranked in order of the most beneficial improvement strategy, in one optimisation run.

- The SCORE method offers an opportunity for the decision maker to gain insight into the production system's behaviour, its constraints, and the level of improvement required to reach a certain performance.
- The results from applying the SCORE method have provided the insight that we might need to re-think how we perceive bottlenecks. Alternative improvement strategies can be discovered if we consider other approaches than just finding an operation or station to improve. If we consider methods that can reveal what property or parameter to improve in the system, we will be able to remove the real constraint with a minimum of effort and resources.

Chapter 7.

Industrial application, results and verification

A number of applications for the framework, proposed in Chapter 3, also in combination with the cost modelling introduced in Chapter 4 and the bottleneck/constraints detection technique introduced in Chapter 6 are presented in this chapter. The purposes of these industrial applications are mainly to verify the framework with its connected methods and discover how it can be used and the extent of its usefulness in real decision-situations. Various types of production systems and decision situations have been included, striving for validation through “multiple triangulation” (Denzin, 2009). First, the framework application with MOO on production systems is tested with an increasing degree of post-optimality analysis. Manual and automated assembly systems as well as a transport system are subject to analysis. Then the complete framework with cost optimisation is applied and verified on a machining line that produces components. The new bottleneck detection method is applied on a complicated production line. Furthermore, opportunities with the new methods are somewhat extended from what was proposed in earlier chapters. The possibilities of extracting information about the level of improvements required when working with bottlenecks are investigated and the ideas around rule extraction are further expanded. Finally, post-experimental analysis and post-optimality analysis are explored with regard to extracting rules to be used as decision support or to enhance the performance of subsequent optimisations.

7.1 Production systems MOO

In this section, the framework proposed in Chapter 3 is applied on three real-world problems, in order to verify the basic functionality, with optimisation of some common

production systems' parameters and objectives. An increasing amount of post-optimality analysis is introduced through these studies.

7.1.1 Manual assembly system optimisation

Competition in the automotive industry moves forward and alternative production concepts emerge. Within assembly systems development, the walking-worker concept has been noticed as an interesting approach to level capacity to customer demand. One of the main disadvantages has been that each worker has to learn a great deal about the work covering all stations in the line. This application study investigates an approach with a sections of line divided into worker loops, in order to overcome some of this disadvantage while maintaining the effectiveness and ability to align capacity to customer demand.

7.1.1.1 Introduction

The automotive industry is constantly striving to improve production performance in a very competitive business situation. In line with the significant and frequent fluctuations in customer demand of the last few years, alternative production concepts are emerging. Within assembly operations, the traditional setup of one or more workers dedicated at each station, illustrated in Figure 1, is challenged by other concepts such as walking workers that follow the assembly object through the line (Wang et al., 2005), as shown in Figure 2.

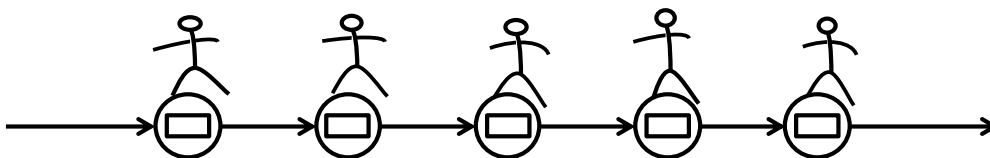


Figure 7.1. Traditional assembly line.

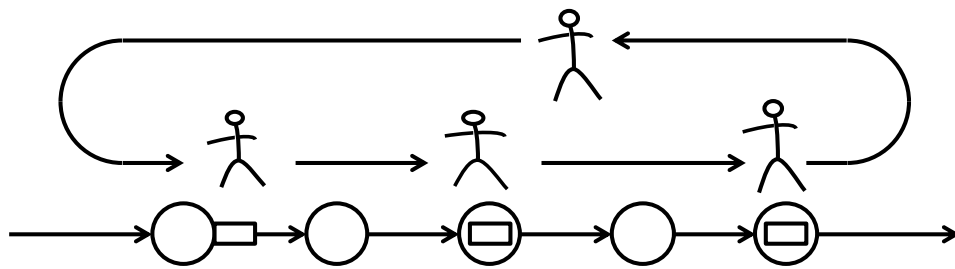


Figure 7.2. Walking-worker assembly line.

An alternative setup to having workers follow the assembly object is to use fixed positions without moving the work items (Huang et al., 2007), e.g., for fragile, bulky or heavy products. Another variant is to have multiple multi-function workers serving parts of a u-shaped line (Nakade and Ohno, 2003). However, in this application study the focus is on workers moving along with the assembly object. The walking-worker concept has many advantages including cross-trained workers, less WIP with fewer buffers, improved worker accountability, and robustness against station time variations, as shown by several studies (Wang et al., 2009, Wang et al., 2005, Mileham et al., 2000). Nevertheless, there are also some disadvantages, such as pronounced training requirements for workers and a higher potential for blocking due to workers performing at a lower level. The main advantage of the walking-worker line concept is probably that it provides the opportunity to align the assembly capacity to the customer demand (Wang et al., 2005), by varying the number of workers on the line without the need to rebalance and make physical changes to the line setup and the material facade. The capacity can be adjusted from just having one operator on the line to having the number of operators match or surpass the total number of stations. The concept is considered a concept within reconfigurable assembly systems (Bi et al., 2007). It has been shown (Wang et al., 2005) that walking-worker lines are quite robust against the effect of disturbances, if the number of workers is kept somewhat lower than the number of stations, enabling higher throughput with the same number of workers compared to traditional setups. However, as the number of workers approaches the requirements for maximum capacity, the negative effect from variation sources becomes more evident in limiting throughput. It has been shown that simulation modelling and a combination of

optimisation techniques can be an effective tool for designing walking-worker assembly lines (Alzuheri et al., 2010). The expected capacity from a specific number of workers can be studied by using simulation (Wang et al., 2007) and repeated simulations for each possible number of workers can provide a complete mapping of all the available capacity steps. Balancing the system with respect to the required amount of training and the ability to align capacity with customer demand is a serious challenge for enterprises, when designing, dimensioning, and implementing walking-worker lines. During the past years, SMO has emerged as a very useful tool for decision support within production systems design and improvement (Ng et al., 2012, Pehrsson et al., 2011 and Pehrsson et al., 2011). The opportunity to use this method to solve a task that concerns the optimised manning of a sectioned walking-worker line is explored in this section.

7.1.1.2 Application study

During the improvement of a mixed-model (Sarker and Pan, 1998) walking-worker assembly line within an automotive manufacturer, the project team was challenged to reduce the worker training requirements, while maintaining the opportunities to align capacity to customer demand by varying the number of workers on the line. Behind this challenge was an expectation from management to improve quality and to increase the capacity as a result of less worker-related abnormalities, errors, and station time deviations. The idea to divide the line into two or more walking-worker sections was then raised. This entailed that a majority of workers only had to be trained to perform a limited number of operations. The flexibility to follow customer demand and align capacity accordingly would still be covered, even though some limitations might occur. However, some of the workers could still be trained to master all operations on the line, which would compensate such limitations. Since no major hardware changes were required to try this method, a test was rapidly executed after the idea emerged. The line was divided into two walking-worker loop sections, as illustrated in the before and after in Figure 7.3.

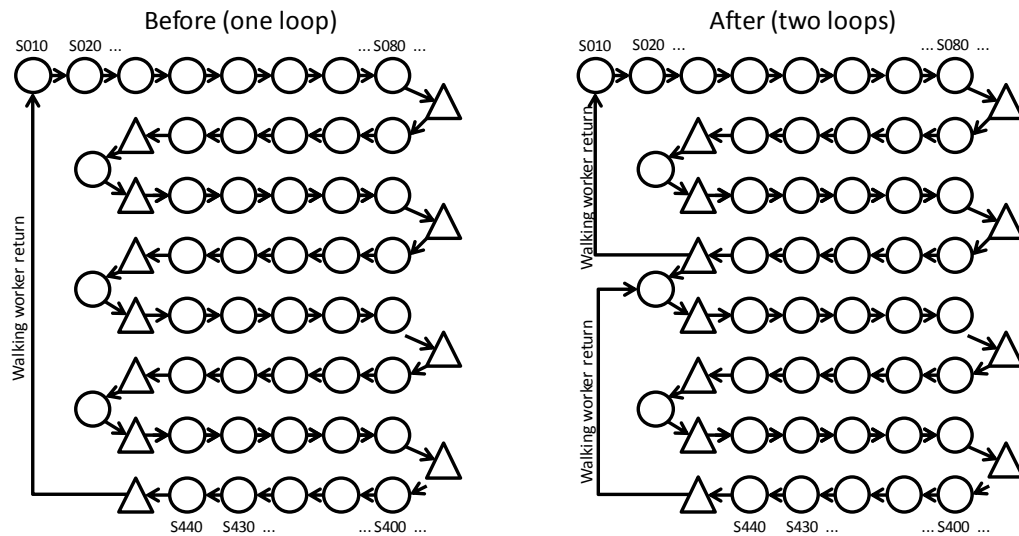


Figure 7.3. Before and after sectioning the line into two loops

The workers for these new sections were divided equally into two teams and production started. However, the throughput from the line did not increase and actually declined. Finding out more about the causes of this system behaviour was considered a problem suitable for analysis with the help of SMO and a case study was initiated. Since management wanted quick results from the improvement team and the SMO analysis, a simulation model of the line with reduced complexity and aggregated data was created with FACTS analyser (Ng et. al., 2007), in order to enable the creation of valuable decision support within an acceptable timeframe. The simplifications made to the model were to assume that all the workers on the line would perform at the same pace and with the same type of variation pattern at all stations. By doing this, the line could be modelled with standard operations, requiring only cycle time, availability, and mean downtime data together with a pallet system carrying the products. The pallets could then mimic the worker moving with the object, since an assembly object was always released onto the line together with a worker. Pace variation for a worker or between workers (Sakamoto, 2010) in combination with the workstation effectiveness can be integrated into the simulation model through station cycle times with variation. The cycle time variations in this case study were aggregated and modelled using a triangular

distribution with min mode max parameters for each assembly station. Cycle times for all stations with min, mode, and max related to the triangular distribution can be found in Appendix 1.

Availability was set to 99% and MDT to 30 seconds for all stations, based on data from the company. A review of the data in Appendix 1 can also reveal that there was some imbalance between station cycle times. The study was also limited to include the most common variant on the line, produced 60 to 70 % of the time.

Both the before and after scenarios were simulated with a total of 26 workers and five replications. The results were strikingly comparable to the real line behaviour, showing 34.2 jobs per hour (JPH) in throughput for the original line and 31.9 JPH for the segmented line, compared to the real-life result of 33 JPH vs. 31 JPH, as stated by the production manager.

However, the results could still not answer why the throughput and the capacity decreased when the line was segmented into two walking-worker loops. Theories about blocking and starving between the two segments were discussed, but could not be verified through the simulation models. Nevertheless, when SMO was applied with regard to minimising the number of workers per loop while maximising throughput, some interesting knowledge about the system was revealed, as shown in Figure 4.

Solutions were revealed showing the same throughput performance for the one loop system and the two loop system with an equal total number of workers. There were actually some solutions that surpassed the original solution with respect to throughput. Hence, not only the stations must be balanced when moving from a one loop system to a two loop system, the loops must also be balanced, e.g., by releasing the right number of workers into each loop.

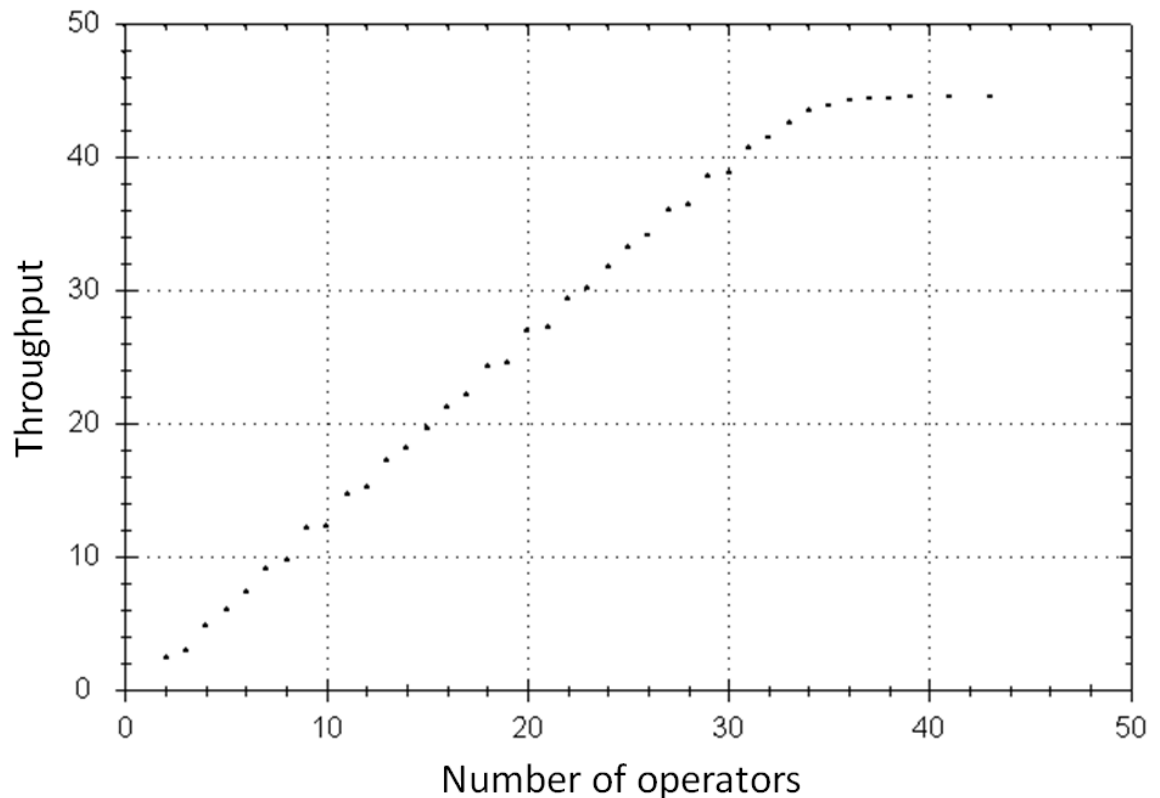


Figure 7.4. Results from the SMO-study with optimised number of workers per loop.

When the line was divided into two segments, the amount of station time for each segment was not considered and, due to an imbalance of station time between the two segments, the throughput was restricted because more work was put on the workers in one loop, causing idle time in the other. One way to address this problem is to assign the optimum number of workers per section; another might be to level out the station times between the loops through re-balancing the work content. In this case the loop imbalance could be used to advantage, as some steps in the number of workers will actually result in higher throughput. The required throughput in this case could be achieved with fewer workers, after dividing the line into two walking-worker loops. A recipe for correct manning could be created, so that capacity can be smoothly aligned to customer demand. See Appendix 2 for an example with detailed figures.

Two sets of benchmark simulations with completely balanced station times were run, in order to quantify the amount of loss caused by deviations in station times and to compare the existing situation with the performance of the system under ideal or close to ideal conditions. The results from the benchmark simulations are shown, together with the simulations of the original setup, the sectioned line setup and the sectioned setup with a balanced number of workers in the two loops, in Figure 7.5. A comparison between the scenarios shows that the effectiveness of the system, with a specific number of workers and imbalance, can be kept at considerably high levels, as long as the line is operated at throughput levels below the total limitation of the balance. The system utilisation decreases close to the maximum throughput. These findings correspond with those of other studies (Wang et al., 2009 and Wang et al. 20005).

Balancing the number of operators between the loops enables the performance of the two loop system to be on a par with the one loop system. It also seems that the correctly balanced two loop setup might perform somewhat better than the one loop setup. The differences are very small indeed and there are probably other factors such as worker training, efforts and skill that will make the real difference. Future studies will have to show whether the sectioning of the line and reduced training requirements will enable assembly operations that have less disturbances due to improved worker performance.

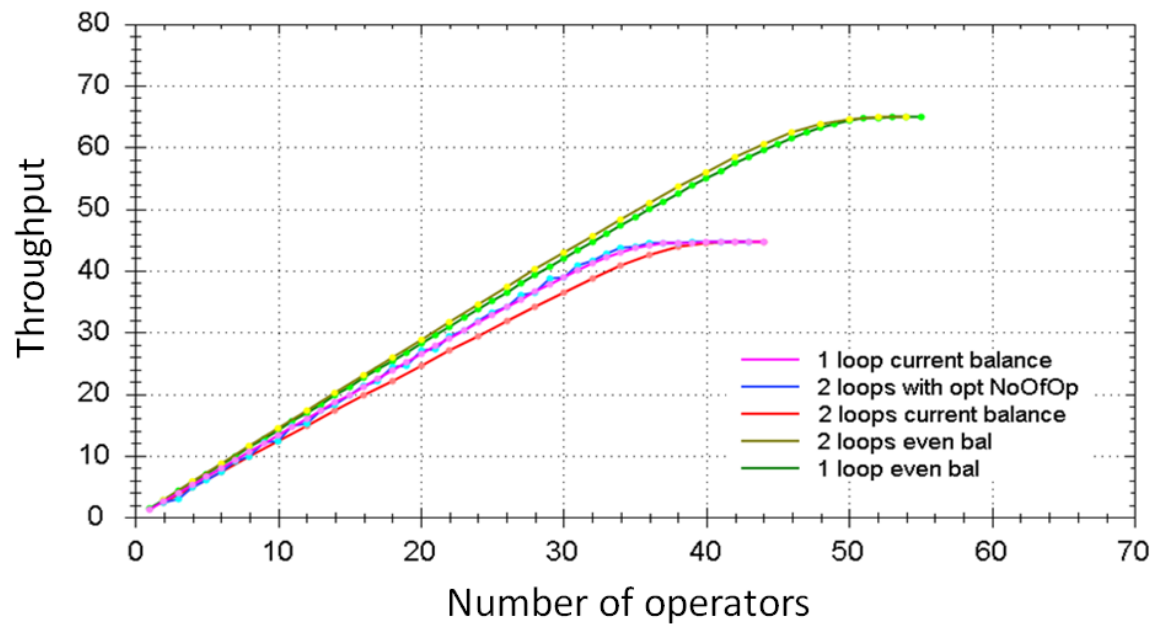


Figure 7.5. Results from simulations and optimisation of the number of operators per loop.

7.1.1.3 Findings

Walking-worker lines have the ability to maintain effectiveness at reduced throughput levels, as well as align the number of workers and the capacity to customer demand. Some of the disadvantages with extensive training requirements can be offset by assigning the workers to work in loops covering parts of the line, while maintaining or slightly improving the overall performance of the system. The robustness towards disturbances in a walking-worker assembly system seems to be very useful, when operating lines with imbalance and fluctuating customer demand. The application of MOO can significantly contribute to decision-making, with regard to assembly systems, by revealing information and knowledge.

7.1.2 Automated assembly system analysis and optimisation

The main intention with this application study was to explore the opportunities of using SMO for the analysis of production system behaviour. An assembly line was designed

with a pallet system loop for transporting the main assembly object. Previously, the line has been the subject of a case study concerning the optimisation of the number of pallets in the main assembly loop combined with innovation (Ng et al., 2009). However, in this extended case study, a secondary pallet system, used to replenish the line with components for assembly, was observed together with the main system, for the purpose of explaining the overall system behaviour. The components handled by the secondary pallet loop need to be classified separately from another assembly object, due to tight tolerances. When the incoming components are loaded onto the secondary pallet system, information about component classification is sent upstream in the main process. Material at the upstream receiving location is not allowed to continue in the flow unless the required classification information is available, in order to assemble the other classified component. This creates a restriction, from a WIP perspective, in the main flow modelled as a max-WIP loop, dependent on the number of identified components buffered on the secondary pallet system. A simulation model of the line was created and, after validation, the optimisation objectives were integrated into the model using the SMO framework. The optimisation objectives that were expected to reveal the system behaviour were (7.1):

$$\begin{aligned} nm & \text{ (min)} \\ ns & \text{ (min)} \\ \varphi & \text{ (max)} \end{aligned} \tag{7.1}$$

where, nm = the number of pallets in the main loop, ns = max-WIP due to identified components on the secondary pallet loop and φ = throughput.

By plotting the three objectives after optimisation, as seen in Figures 3 and 4, some insights into the system behaviour can be revealed.

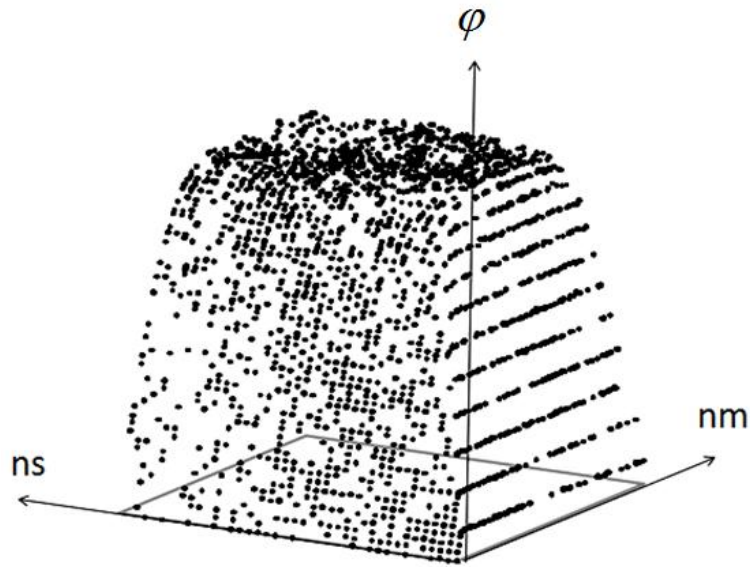


Figure 7.6. Three-dimensional plot of the main decision variables and their effect on throughput.

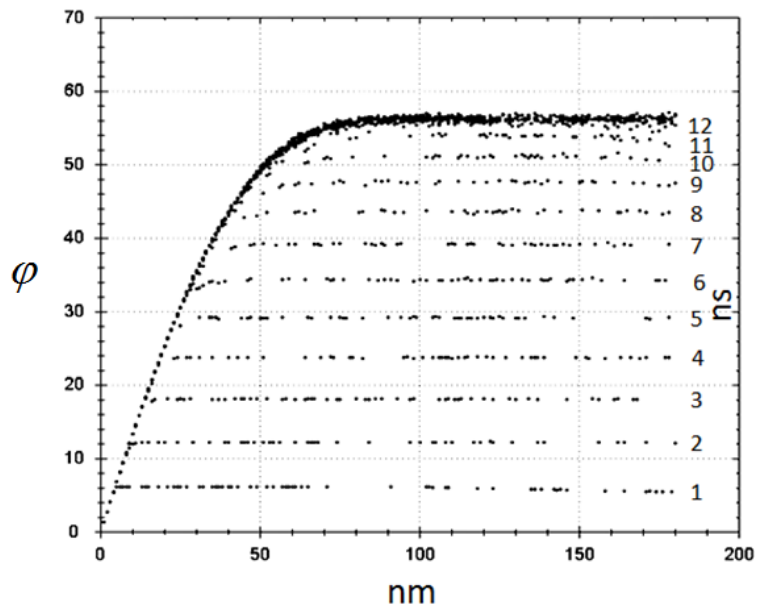


Figure 7.7. System behaviour plot showing the dependencies between the number of pallets in the main Loop, the Max-WIP loop and throughput

At least 12 identified components with information sent upstream are required, in order to reach maximum system performance from a throughput perspective. The flat top of the curve indicates that there was some other constraint limiting the throughput of the line. A shifting bottleneck analysis (Roser et al., 2002) showed that some stations were significantly restraining the capacity of the line. With improvements targeted for these specific stations, the maximum throughput could be increased by 14%. The drawback was that the number of identified components required for the secondary pallet loop increased from 12 to at least 17 and with some further improvements to over 20, which brought the maximum practical buffer of 24 very close. Since keeping the buffer operating at that level would require an extra dedicated operator on the line, it was decided to remove the max-WIP constraint, by moving the assembly of the two classified components to a station further downstream in the assembly line. After implementation, the relative effect on throughput was observed and it conforms very well to the figures from the optimisation.

7.1.2.1 Findings

The conclusion is that MOO can be a powerful method to extract knowledge about production system behaviour, serving as an important source for the creation of decision support within industry.

7.1.3 Decision-making in conceptual AGV-systems design

The framework, proposed in Chapter 3, is applied on a real-world problem related to the conceptual design and analysis of an Automated Guided Vehicle (AGV)-system. Several methods for post-optimality analysis are used to extract decision information.

7.1.3.1 Summary of the study

In order to shorten the development lead-time and enable the evaluation of many alternative conceptual scenarios, the use of aggregated modelling techniques is required. On the other hand, it is believed that well-informed decision-making in conceptual production systems development can be elevated to a new level through the application of MOO together with techniques for post-optimality analysis and Visualisation of high-dimensional data. An industrial case study regarding the conceptual design of an AGV system has been carried out to evaluate the usefulness of such a combined methodology. The case study, based on a real-world industrial decision-making problem, demonstrates how knowledge can be extracted from optimisation data in order to support decision-making which cannot be easily done with other industrial practices.

7.1.3.2 Introduction

While analytical methods like Petri nets (Castillo et al., 2001) and queuing models (Sang and Kwon 1994) can effectively be applied to AGV systems design, simulation (in particular discrete-event simulation) is still the most practical choice for industrial practitioners (Tempelmeier 2003)(Vis 2006). This is not a surprise when considering that any complex products mix and their routings can easily be modelled using almost any simulation software. On the other hand, simulation is not an optimisation tool when used on its own. The connection of meta-heuristic search methods to simulation models, referred to as SBO, can be used for finding the optimal setting of many decision variables in a design optimisation problem (Law and McComas, 2002). Despite the potential of finding optimal or near optimal solutions that SBO has opened, the task of finding essential parameters, design principles, and relations within data from SBO can be very time-consuming and daunting. The concept of innovation through optimisation referred to as innovization, as introduced by Deb and Srinivasan (2009), incorporates post-optimality analysis on the solution sets generated from MOO, in order to reveal essential design rules hidden in the Pareto-based optimal solutions. By integrating advanced visualisation techniques of high-dimensional data, for example, Mosaic plots,

PC plots, and other glyph-based plots (Liebscher et al., 2009), into the “innovization” process, it is believed that decision-making can be supported by an elevated knowledge of the system.

The type of aggregated conceptual production systems modelling and optimisation approach applied in this section can be used to integrate several production lines, transport solutions, and logistic systems into one model. FACTS Analyzer (Ng et al., 2007), or FACTS hereafter, as a conceptual factory modelling and simulation tool, which has built-in MOO support for production systems design problems, has been used throughout the study. Previously, we have reported the use of FACTS in a comprehensive, industrial cost optimisation study (Pehrsson and Ng, 2011). The purpose of this study is to demonstrate how post-optimality analysis and visualisation techniques can support the innovization process, in order to gain insight that supports decision-making, by analysing AGV based transport system which connects several new production cells. An essential part of the problem was to quickly analyse different alternative options, in order to decide whether the concept with an AGV system should be further developed or whether alternative solutions should be considered.

7.1.3.3 Industrial application

In contrast to other recent simulation studies of AGV system design, (e.g. Duinkerken et al., 2006)(Klaas et al., 2011), which are more focused on routing strategies, the main task involved in this case study was to evaluate and optimise the required number of AGVs and inter-station storage capacities. These are the most important parameters to be selected during the decision-making of the conceptual phase of the production system design for further development. An AGV system can be fairly costly and the number of AGVs has to be kept to a minimum, in order to reduce the total investment cost. DoE is a common approach used to address this level of optimisation. Similar to the innovization approach, DoE facilitates the optimisation and analysis of the number of AGVs and their relationship with other design variables (or factors using the term in

DoE); see Gebennini et al., (2008). Nevertheless, as this section reveals, innovization can offer a powerful, yet more interactive and intuitive approach to gain insights into solving the design problem than DoE.

7.1.3.3.1 System Data

As input for the study, a conceptual layout of the production system, including all distances, was used together with information on AGV performance, such as speed, battery capacity, and charging time.

The capacity and throughput figures of each connected line were aggregated and described through cycle time, availability, MTTR based on separate simulation and optimisation of the individual lines. The availability and MTTR of the AGVs were also considered and the storage was defined by capacity and transport time. The actual parameter values can be found in Table 7.1.

Table 7.1. Parameter values in the simulation model.

Object	Cycle time	Availability	MTTR
Line A	120	75	25
Line B	80	75	25
Line C	90	75	25
Line D	229	84	25
Line E	55	85	5
Line F	55	85	5
Pick up A	66	99	5
Pick up B	66	99	5
Unload	66	99	5

7.1.3.3.2 Modelling

As a conceptual model, the FACTS simulation model was built following the logical flow of the AGVs, rather than their actual movements. Standard FACTS objects, such as operations and buffers, were used in combination with flow logic to represent the behaviour of the AGV system. The carriers were modelled using the standard pallet

objects; see Ng et al., (2011) for a list of the standard FACTS objects. The completed FACTS model is shown in Figure 7.8.

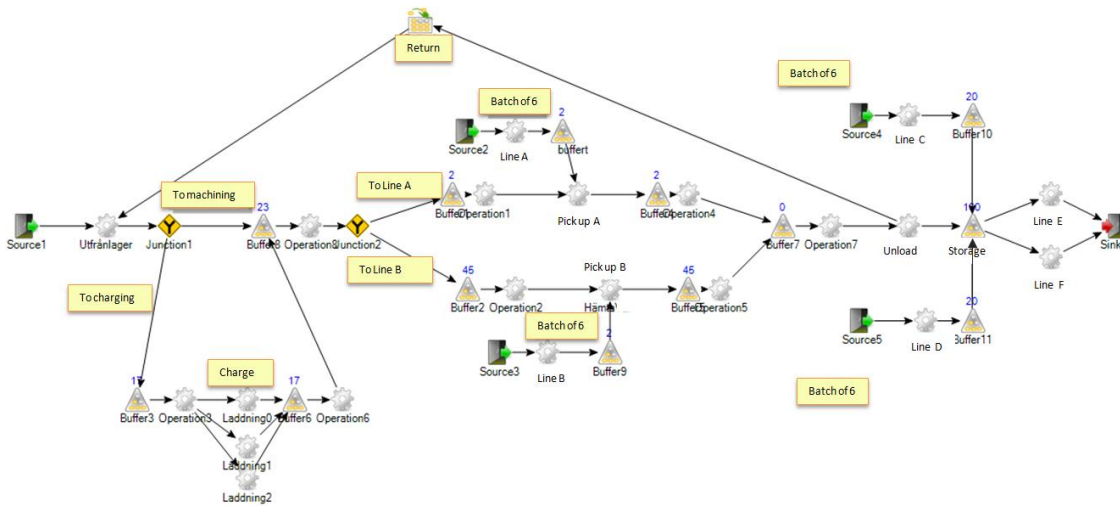


Figure 7.8. Conceptual flow model of the AGV system and the main production system.

The average speed of an AGV and the distances from the layout were recalculated into transport times and included in buffer objects. The capacities of these buffers were set to mirror the maximum number of AGVs that it was possible to “store” along each transport, according to distances taken from the layout. Junctions were used to emulate the flow logic and the routing was aggregated into percentages of the AGVs following a part of the flow. A maximum of three battery charging stations were planned and 5% of the AGV flow would follow the charging route and stay at a charging station for one hour at a time. A 40% share of the AGV flow was to pick up products from line A and a 60% share was to pick up products from line B.

7.1.3.3.3 Stage 1 Optimisation

An optimisation of the system was performed employing the widely-used NSGA-II algorithm (Deb et al., 2002) with 1000 simulation evaluations (each 5 replications). The input parameters were the number of carriers, with range [1, 10], and the storage capacity [0, 1200]. The main objectives were to simultaneously minimise the number of carriers, minimise the storage capacity, and maximise throughput.

7.1.3.3.4 Stage 1 Analysis

The throughput was above various storage capacity levels, depending on the number of AGVs released into the system. With a storage capacity larger than 150 units, the system was found to be stable from a throughput perspective. Filtering the data for solutions that had a storage capacity larger than 150 units revealed nine clusters, each with a number of solutions that had the same throughput in common. By observing the decision-space parameters for each cluster, it was found that each specific number of AGVs in the system was connected to a corresponding cluster. Three and four AGVs ended up in the same cluster, limiting the total number of clusters to nine. Hence, the number of carriers was identified as the main factor affecting the system throughput. The highest throughput was achieved by investing (or releasing) six carriers into the system.

7.1.3.3.5 Visualisation

With a stabilised throughput secured by a correctly dimensioned storage, the number of AGVs clearly constrained the system throughput to certain levels. This can be seen by the lines in the scatter plot showing the optimisation results in Figure 7.9. The values on the right-hand side of Figure 7.9 show the number of AGVs with the corresponding throughput.

Six AGVs would be required to reach the maximum throughput achieved by the optimisation of the system. With just one AGV, the throughput only reached 83.5 JPH and although 94 JPH could be achieved using two AGVs the decision was to investigate alternative solutions.

The actual throughput objective was to reach a total of 100 JPH from lines A, B, C, D, E and F. In order to achieve that goal, other aspects of the system had to be considered for re-design. The result was somewhat unexpected and required deeper analysis.

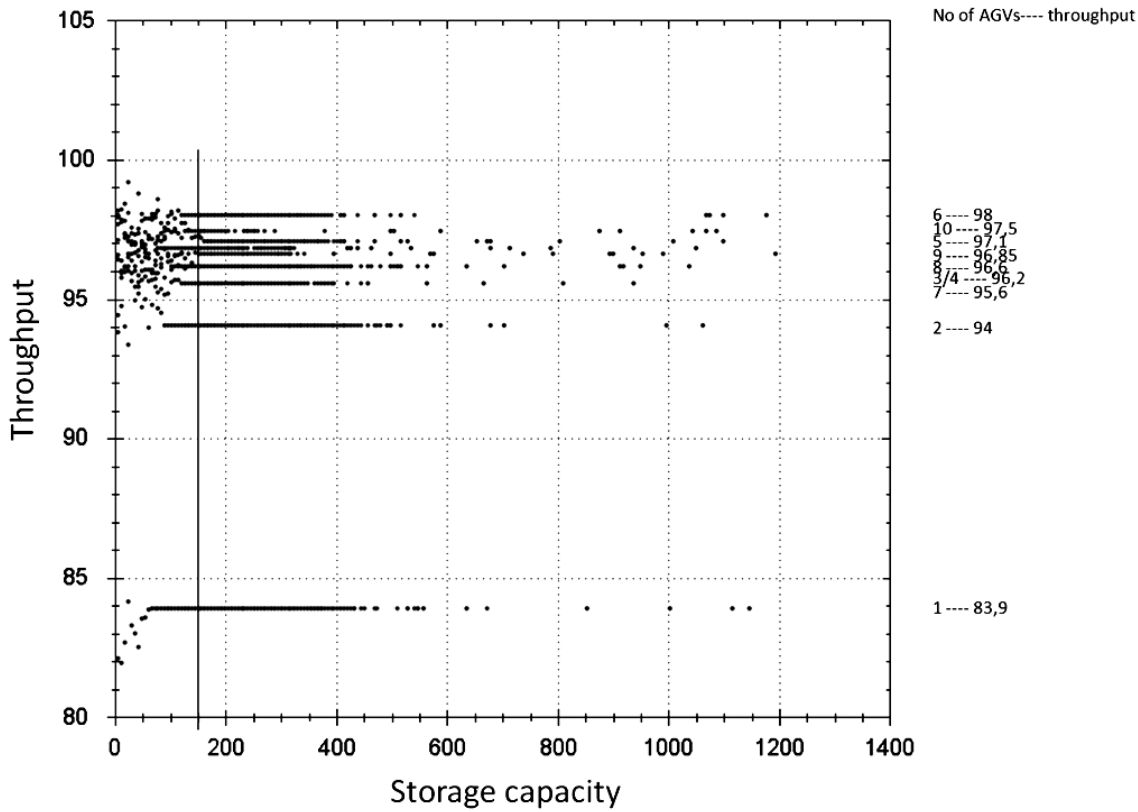


Figure 7.9. Initial optimisation results.

7.1.3.3.6 Mathematical Modelling: A comparison

A mathematical method for the dimensioning of AGV systems (Groover, 2008) that had even more of a conceptual analysis nature was applied. The required number of AGVs (nc) can be estimated by calculating the average AGV work load (WL) and the available time (AT). The estimated nc is then equal to WL/AT . In this case, the result of the estimation was $nc = 0.97$. In other words, only one AGV would be required. The capacity would, however, be somewhat limited with only one AGV, considering that a 60-minutes charging time is required every 20 hours. The combined theoretical hourly capacity for lines A and B would be reduced from 56.25 JPH to 53.44 JPH. The theoretical capacity for lines A and B was also confirmed to be 56.25 JPH by a deterministic simulation (with the availability included as tact time) of the corresponding part of the system with one AGV and no charging. Based on this, the

recommendation from the mathematical study would be to invest in two AGVs. There were, however, other parameters in the system that could be considered for optimisation. The capacity of the buffers on the output conveyors from lines A and line B were such parameters. The stochastic behaviour of Lines A and B with 75 percent aggregated availability and 25 minutes MTTR might actually require another dimensioning of these buffers. Increased buffers would also be more forgiving of eventual effects from the simplified conceptual control logic when dividing the AGV flow into lines A and B.

7.1.3.3.7 Stage 2 Optimisation

The input parameters for the optimisation were updated to include the capacities of Buffers A and B, with a range of 1 to 10 transport loads of 6 jobs each. A new optimisation, using NSGA-II was run with 1000 iterations, again each replicated five times. The sum of the capacities in Buffers A and B was introduced as an optimisation objective for minimisation.

7.1.3.3.8 Stage 2 Analysis

The data from the second optimisation run revealed some new opportunities. The maximum throughput of the complete system with one AGV increased to 90.3 JPH, with two AGVs to 98.6 JPH, and with four AGVs it would be possible to reach 100 JPH, as shown in Figure 7.10. The graphical analysis of this type of step effect is first presented in Chapter 4 (Section 4.5), then further explored and explained in Chapter 7 (Section 7.4).

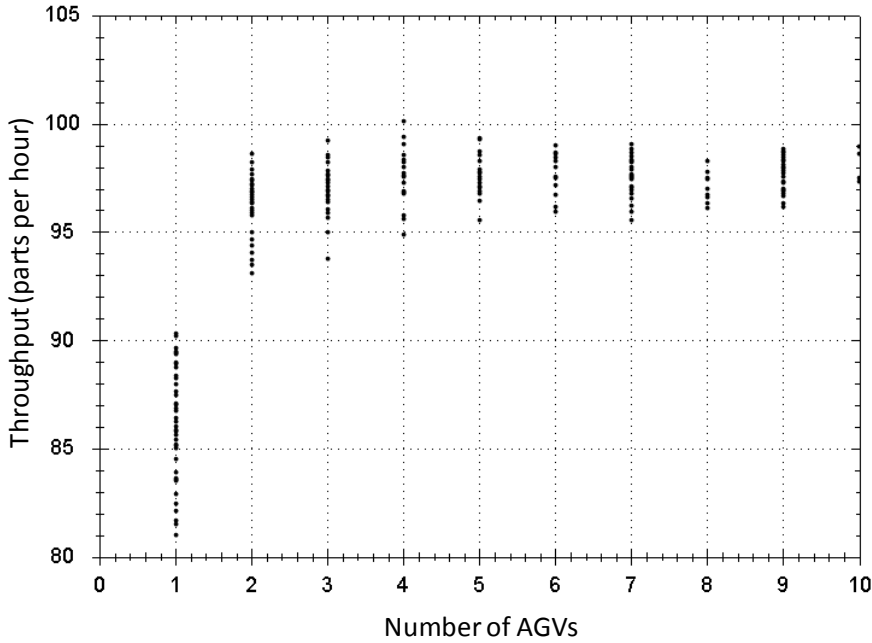


Figure 7.10. Number of AGVs and possible throughput from optimisation run 2.

The interesting question was then what configuration would be required to run the system at a throughput of 98.6 JPH with only two AGVs. In order to reveal more information, the new buffer parameters were plotted against throughput, as illustrated in Figure 7.11. According to these plots, it is possible to reach a throughput of 98.6 JPH with a transport load capacity of just one. This is shown to be valid for both the buffers.

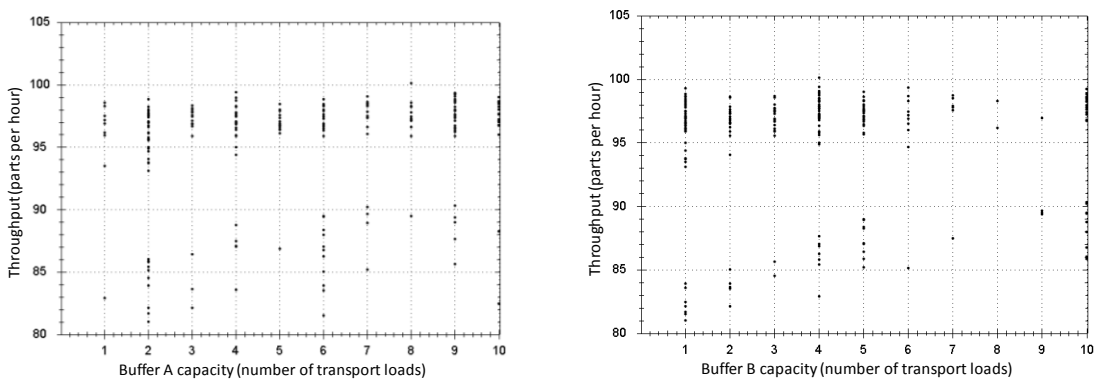


Figure 7.11. Left: Buffer A capacity against throughput. Right: Buffer B capacity against throughput.

Apparently, more information is required in order to make an informed decision. By plotting the optimisation objectives on a 4D graph (3D plus colour), shown in Figure 7.12, some insight into this industrial problem can be obtained. A study of the two clusters in Figure 7.12 reveals that there is apparently some interaction effect between certain parameters which can leverage the system to reach the desired performance trade-off. It will be possible to find solutions with 2 AGVs, an acceptable throughput level, and one of the Buffers, A or B, at one transport load, as long as the sum of buffers, $A+B$, is large enough.

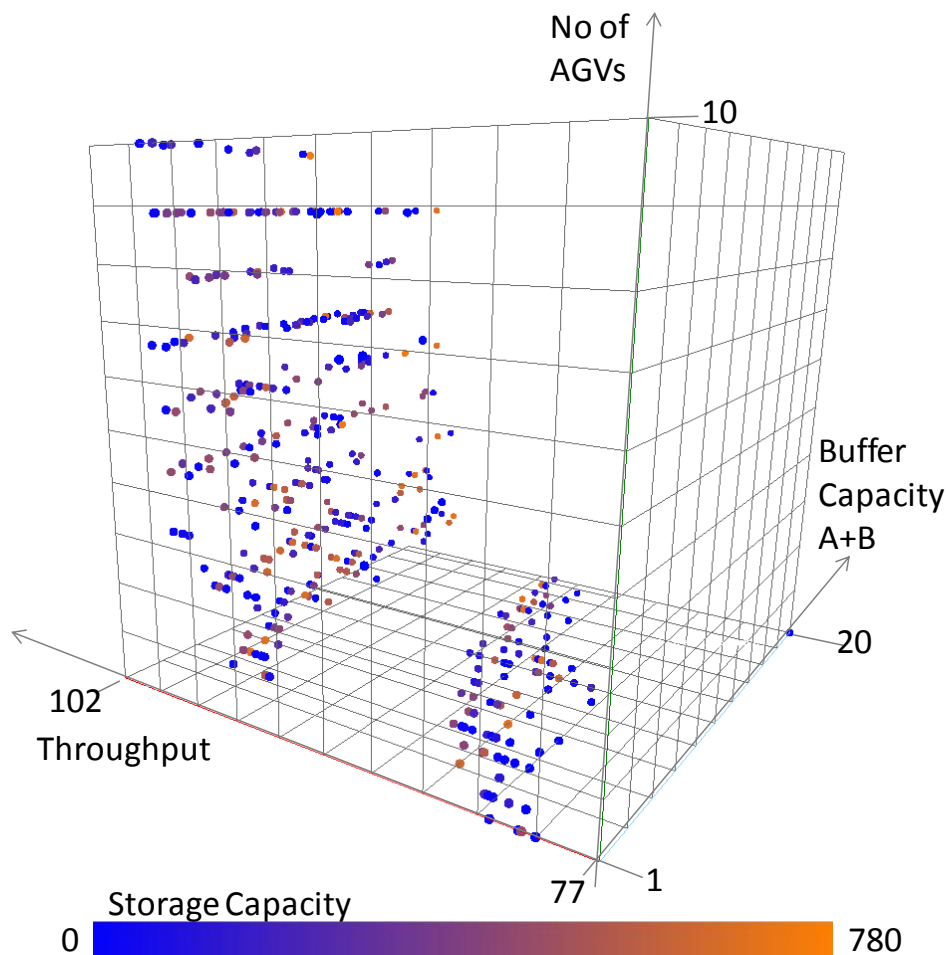


Figure 7.12. 4D plot of the objective space.

Even more information about the system can be revealed by using a PC plot, as shown in Figure 7.13, which connects objective space parameters with decision space parameters. By filtering out solutions with throughput above 98.5 JPH and storage capacity smaller than 50, it becomes obvious that the number of AGVs required in the system will be 6 or 7, the Buffer A capacity must be 9 or 10, and Buffer A+B capacity should be 12 or 13. The main problem with these results is the amount of AGVs required.

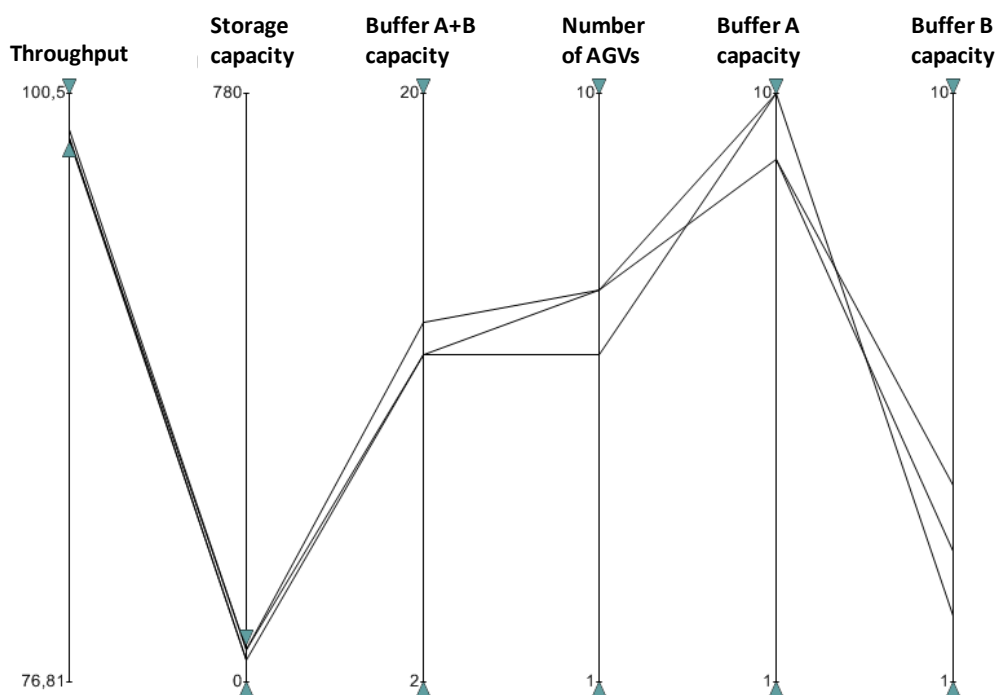


Figure 7.13. PC plot focusing on high throughput and small storage.

If the data is filtered for solutions with throughput more than 98.5 JPH and the number of AGVs less than 3, another trade-off is to be found. This is illustrated through the PC plot in Figure 7.14. By increasing the storage capacity to somewhere between 340 and 535, while Buffer A capacity is kept at 10, the objectives for throughput and AGV number can be met.

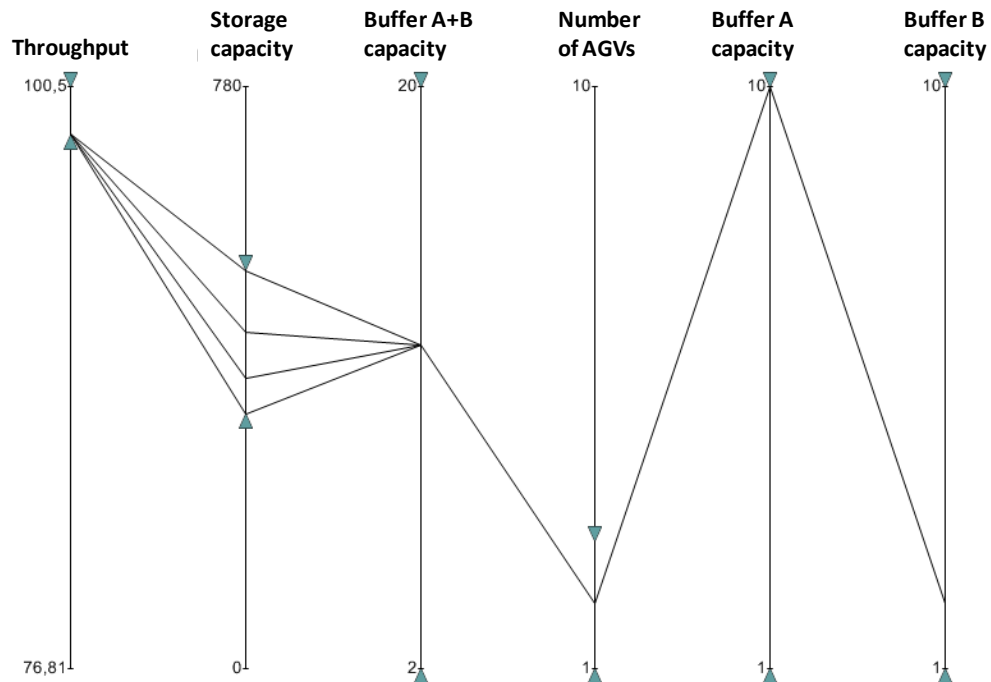


Figure 7.14. PC plot focusing on high throughput and a small number of AGVs.

7.1.3.3.9 Decision-making

The number of AGVs required to operate the system at sufficient throughput with an acceptable dimensioning of the storage capacity was considered to be too high to motivate the investment in AGVs. The relatively large Buffer A, shown to be important to fulfil the other objectives, was not really a feasible solution when layout issues were considered. Finally, an alternative layout was found to be much more favourable and the investment in an AGV system could be avoided.

7.1.3.4 Findings

The use of a combination of post-optimality analysis and advanced visualisation techniques, such as 4D and PC plots, has proven to be very useful for the extraction of essential parameter settings from optimisation data and to gain knowledge about the problem, in order to support decision-making. This is demonstrated through applying such an innovization process to a conceptual, aggregated, logical flow model of an

industrial AGV system. The target was to optimise the number of AGV required, together with the simultaneous optimisation of the inter-station storage capacities. An imperative finding was the importance of including enough parameters to truly optimise the system. The application of a mathematical model for the same problem has also been performed in this study and compared with the results from the first stage of optimisation. It has been found that the results obtained from the mathematical model could also be used to improve the setup of the optimisation problem, by including only the essential parameters in the subsequent optimisation stage, in order to find more favourable trade-off solutions.

7.2 Industrial Cost Modelling for Multi-Objective Optimisation of a Production System

In order to further verify the cost modelling method proposed in Chapter 4, it was applied on a real-world problem within the automotive industry. A production line for automotive components with capacity constraints was required to operate overtime (e.g. night/weekend shifts), in order to meet the forthcoming increase in customer demand. At the same time, major product changes were to be introduced in the line. There were a number of potential improvements requiring various investments that could reduce the capacity constraints, potentially providing an opportunity to avoid overtime operations. However, there was not enough information to make a decision to invest and reduce the operating time as well as the cost for labour and production resources. Due to reasons of confidentiality, some of the data used and the results presented in this section had to be concealed and, in such cases, relations in the data have been maintained.

The initially forecasted annual running cost was \$4.9 million (M) and the main objective was to achieve a 20% cost reduction. The challenge was to identify the optimal investment alternatives that would simultaneously reduce running cost, minimise total investment (cost for improvement), maximise throughput, and minimise inter-workstation buffers.

A determination of cost factors was made through an analysis of accounted data from the current production line, together with information about possible improvement options.

The budgeting procedures within a Swedish automotive component manufacturer have been studied, as input for the proposed cost estimation process and as a background for case studies. Historically, the budget was updated on an annual basis, with a sales and production forecast covering 60 weeks of estimations in advance and a long range plan covering sourcing, estimated volumes and product mix for the next five years, including change orders, new product introductions, as well as the phasing out of old products. In combination with such data, the past years' actual performance can be used as input to

the cost model, together with manning forecasts based on Standardised work, Methods Times Measurement (MTM) studies, and line balancing. Market prices for resources consumed are monitored and included in the process. The trend, however, seems to be towards a more continuous budget updating process performed several times a year, but still based on the same type of input as before. An example of a budget, with cost categories and their annual share, from a real-world machining line, is shown in Table 7.2.

Table 7.2. Budgeted cost categories in a real-world machining line

Budget Cost Category	Share %
Scrap	2,3
Wages	32,5
Bought hours	12,1
Process media	1,3
Supplies	2,2
Tools	7,9
Machine maintenance	15,6
Tools maintenance	4,6
Bought services	0,3
Others	0,3
Depreciations	22,9
Crediting	-2,0
Total	100

When running and managing the system, all costs except depreciations are controlled, in order to be as close as possible to fully variable in relation to production volume. There are some step effects to take into account, e.g., when changing the number of shifts or the manning, in order to align the capacity to customer demand. In some cases, when the system is being operated with throttled capacity, the process of media supply facilities might still be running close to the requirements for full capacity. The share of some costs, such as scrap, tools, and maintenance, might increase somewhat with throttled capacity, due to an increase in the work content for the operators, but these effects seem to be mostly theoretical and the costs on average are considered to be aligned with production volume. When overtime is used to compensate a lack of capacity or is chosen instead of additional shifts, the hourly cost for wages is higher,

due to the overtime compensation agreements. There are also agreements for various types of shifts, with compensation for late hours, nights, and weekends. The variation in cost per operator and hour of work compared to a daytime shift can be found in Table 7.3.

Table 7.3. Cost per operator and hour of work on various shifts.

Type of Shift	Cost per hour (%)
Day	100,0
Evening	128,3
Night	160,9
2-shift	116,2
4-shift	137,1
Weekend day	177,0
Weekend night	196,1

The additional cost for overtime can be seen in Table 7.4.

Table 7.4. Cost for overtime for workers from various shifts in percent related to daytime shift salary.

Ordinary type of Shift for the worker	Overtime Cost per hour related to daytime shift (%)		
	Mon-Fri	Non scheduled ordinary day off	Sat-Sun
Day	142.1	156.0	165.4
Evening	170.2	184.1	193.5
Night	203.0	216.9	226.3
2-shift	158.3	172.2	181.5
4-shift	179.1	193.1	202.4
Weekend day	238.0	251.9	261.2
Weekend night	218.8	232.7	242.1

When studying Tables 7.3 and 7.4, it can be concluded that a reduction of the required operating hours for a production line could be a beneficial strategy, since the cost for operators on additional shifts and overtime is more expensive. This type of information combined with balanced manning at predefined capacity steps can be used when aligning the capacity to customer demand or when exploring investment opportunities and improvement alternatives.

The distribution of the costs over the year seems to be quite even, month by month, considering the volumes produced, except for the vacation period in June, July, and August, as shown in Table 7.5. Variations occur, e.g., due to maintenance issues, quality variations, and wages during vacations.

Table 7.5. Real-world example of cost distributed month by month for one year.

Cost distribution and volumes over the year		
Month	Annual cost share (%)	Annual volume share (%)
January	8,9	9,0
February	8,8	9,0
March	9,1	10,0
April	8,4	9,1
May	8,7	9,1
June	9,5	7,6
July	6,0	2,2
August	8,1	7,2
September	8,8	9,4
October	7,5	9,6
November	8,2	10,0
December	7,8	7,9

By defining throughput intervals with operating scenarios, and calculating their average hourly cost, they can be used to optimise the system's development initiatives for the conflicting objectives of running cost and investments (improvement costs).

Another consideration to be made is how to vary and balance the workforce for the short and mid-term. The last years' situation with financial instability and market fluctuations, as well as difficulties predicting future customer demand and required capacity, has opened up for more flexible agreements on working times. During periods of less demand, workers can be on leave and work fewer hours, in order to "pay back" by working more hours when required during periods of greater customer demand. This is one mechanism that can be used to level out market fluctuations. Another way is to use workers from agencies to level out short-term fluctuations. There are also examples of internal worker pools used to level out the effects of variations in demand between product families produced on different lines and to handle required overhead due to worker illness and time off.

In the conceptual phase of a production system, the effect from various product design options must be evaluated from a production process point of view. The evaluation of product design options and production process design options, for a complicated product and its production process, can be a very daunting task, since the number of potential combinations of such solutions could be huge. The task might become even more challenging, if the production process is designed to handle several products and product variants. In Figure 7.15, the principle of various production process design options is illustrated.

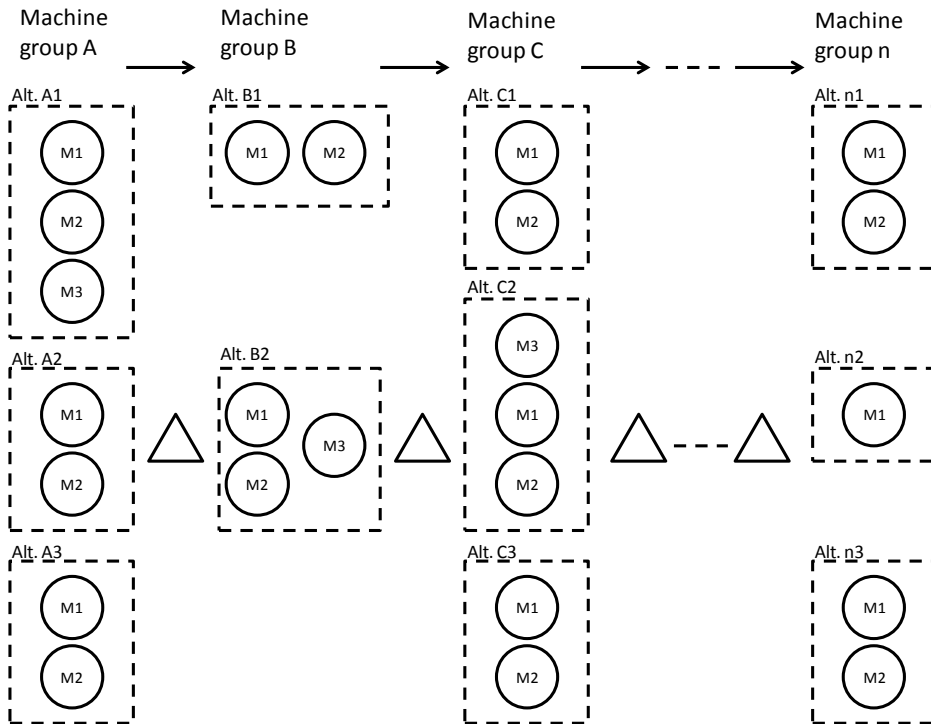


Figure 7.15. The principle with various production process design options.

When considering just the options in the simplified line, according to Figure 7.15, the number of possible configurations will culminate in $3 \times 2 \times 3 \times 3 = 54$, for only four processing steps and a few design alternatives. If the dimensioning of inter-station buffers, minor options for each major alternative, flow, and scheduling opportunities for a complete line are added together with product variants and mix, the total number of combined solutions soon becomes huge and very difficult to grasp with current industrial methods.

The required investments and changes in running costs are estimated for a product change or process change scenario. The investments, expenses, project management cost, implementation cost, and specific running cost influences are calculated for the considered alternatives. A number of sub-categories, shown in Appendix 3, are used to estimate investment and to prepare correct accounting of all related costs.

An existing factory, line or operation is preferably used as a starting point from which differences are calculated. For example, if the setup of an existing machine is to be altered due to a product change and the cutting tool consumption, energy consumption, and the required maintenance is to be reduced, the financial impact of these changes are calculated as a difference compared to the existing system. All other costs are considered to be the same as before. By considering the effect on costs, during the evaluation and preparation of each change option or investment alternative, basic information on the local cost effect can be obtained. Using that information in combination with information from simulations of the complete system will create a more comprehensive understanding of the complete economic effect.

In order to estimate the effect from local changes to production system level or line level, some predictions on the local effect must be made. This includes investments and costs directly related to the changes, as well as the effect on local performance. First, the cost of the changes should be considered, e.g., the investment cost of replacing the machine drive system from supplier A with a new drive system from supplier B. Then, the difference in running cost for the new drive system should be compared to the old drive system. If, e.g., the maintenance cost is lower for the new system or the energy consumption is reduced, it should be taken into account. Thereafter, the resulting production system related parameters, such as machine cycle time, availability, and MDT, should be estimated in order to be used in simulations of the complete system, so that the impact from the local changes on the system performance is revealed. Some help in predetermining where such changes would be most beneficial can be gained through the use of various bottleneck detection methods, such as the Shifting bottleneck Detection technique (Roser et al., 2002) or the SCORE method proposed in Chapter 6. If the manual work content and the standardised work are affected by changes in the production setup, it might be necessary to update the time setting and review the balancing of the line. Based on experience from industry, many production, and maintenance engineers seem quite skilled at estimating the local effect of changes.

However, they often do not use simulation tools and will most likely, as a result, fail to evaluate the effect at line or production system level.

The industrial procedures should be considered when applying cost and investment models for optimisations and when integrating such models into simulation models, in order to secure the availability of the required data.

7.2.1 Simulation Model and Validation

In order to analyse and optimise the production line, a simulation model was created by using FACTS Analyser (Ng et al., 2007), a software tool developed to support factory design, analysis, and optimisation during the conceptual design phase. Initially, the existing production line was modelled for validation of throughput. The model is visualised in Figure 7.16.

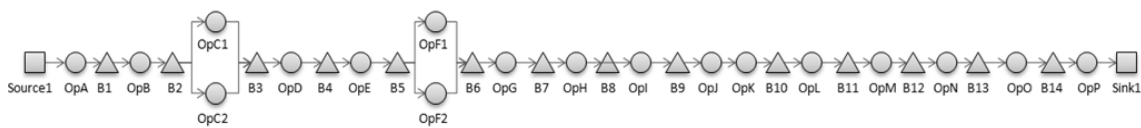


Figure 7.16. Initial simulation model for validation.

The model corresponds to the real production line very well, showing an average model throughput of 17 JPH and a standard deviation of 0.21, compared to the real average throughput of 17 JPH. The validation was based on a simulation horizon of six days, including one day warm-up time. Five replications were used to obtain an indication of the standard deviation.

7.2.2 Introduction of Conceptual Changes in the Simulation Model.

Due to product changes and increasing customer demand, there were plans to introduce major alterations in the studied production line, including partly parallelised flow, as well as a combination of additional new and re-used equipment and the removal of old equipment. The conceptual line was modelled in FACTS Analyser and is illustrated in Figure 7.17.

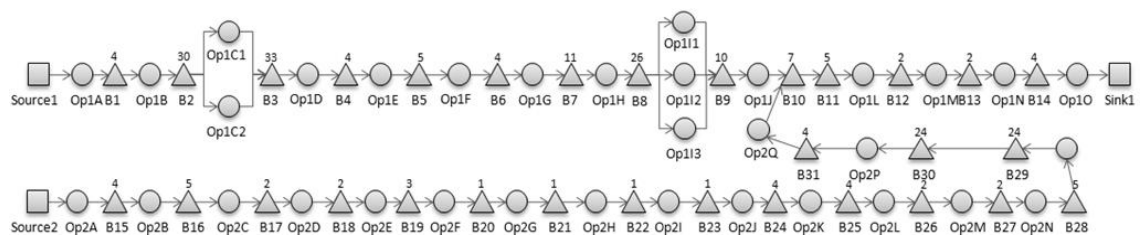


Figure 7.17. Conceptual line configuration model for analysis and optimisation. Allocated buffer capacity is shown in figures above the triangular buffer symbols.

7.2.3 Simulation with shifting bottleneck detection analysis

In order to predict the performance of the conceptual production line and identify major constraints, a simulation with shifting bottleneck detection analysis (Roser et al., 2002) was carried out using FACTS Analyser. The simulation horizon used was 8 days including one day warm-up, with 5 replications. The expected throughput performance was approximately 30 JPH and the simulation result was 28.7 JPH, with a standard deviation of 0.61 and an average WIP of 189. The results were also divided into the two connecting parts of the line, as shown in Table 7.6, in which S1 represents products from Source 1 and S2 represents products from Source 2.

The production volume forecasts indicate that an average throughput of at least 34.5 items per hour is required to meet the customer demand. This is where the shifting

bottleneck analysis, illustrated in Figure 7.18, becomes very useful. By analysing the major constraints of the line, precisely targeted actions can be suggested in order to improve the performance of the production system.

Table 7.6.. Simulation Results

Variable	Mean	Std. Dev.
Parts Produced	4814.40	101.89
Throughput	28.66	0.61
Lead Time (complete system cycle time)	23542.36	696.44
WIP	188.56	1.98
S1 - Parts Produced	2584.40	117.95
S1 – Throughput	15.38	0.70
S1 - Lead Time	33756.04	1687.48
S2 - Parts Produced	2230.00	27.69
S2 – Throughput	13.27	0.16
S2 - Lead Time	11750.50	229.49

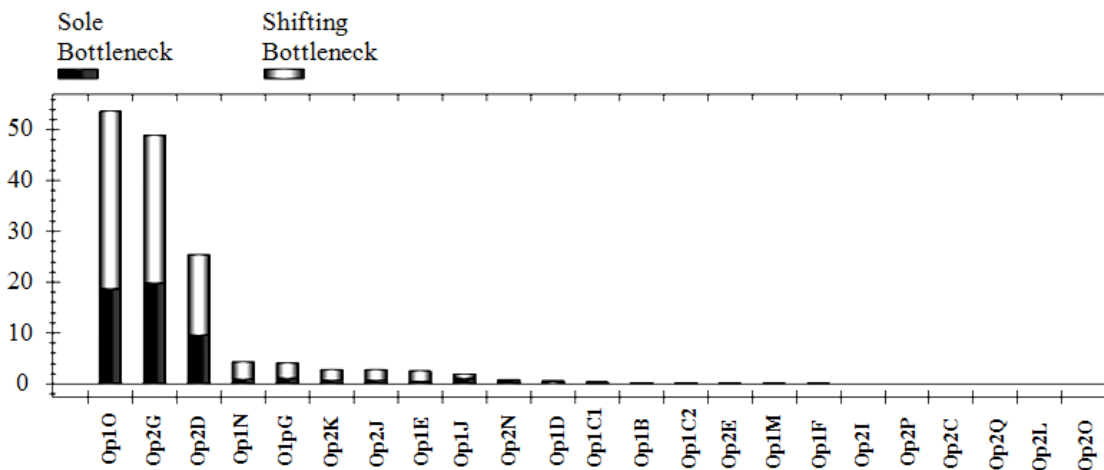


Figure 7.18 Sole and shifting bottlenecks in the conceptual production line.

7.2.4 Production Process Improvement Proposals with Investments

Based on the shifting bottleneck analysis, a number of proposals for potential improvements were obtained from the organisation connected to the line. Emphasis was on the part of the line supplied from source 1, as its throughput potential was considered greater compared to the part supplied from source 2. In this case, the improvements were required to be introduced in a certain order, when applied. That is, up-time improvement 1 has to be introduced before up-time improvement 2 and processing time improvement 1 has to be introduced before processing time improvement 2, in each operation. The relevant improvement proposals obtained can be seen in Table 7.7.

Table 7.7. Relevant Improvement Proposals

Operation and Improvement	0	1	Cost 1 (\$)	2	Cost 2 (\$)	3	Cost 3 (\$)	4	Cost 4 (\$)
Op1E									
<i>Iu</i>	91%	95%	5 443	96%	2 500	97%	4 500	-	-
<i>Ip</i>	145s	143s	10 000	133s	10 000				
Op1G									
<i>Iu</i>	91%	95%	5 000	95,5	2 500	96%	25 000	97%	2 500
<i>Ip</i>	145,3s	138,3s	20 000	-	-	-	-	-	-
Op1H									
<i>Iu</i>	-	-	-	-	-	-	-	-	-
<i>Ip</i>	153s	115s	2 500	-	-	-	-	-	-
Op1J									
<i>Iu</i>	-	-	-	-	-	-	-	-	-
<i>Ip</i>	145s	130s	20 000	-	-	-	-	-	-
Op1N									
<i>Iu</i>	93%	95%	5 000	-	-	-	-	-	-
<i>Ip</i>	95s	80s	20 000	-	-	-	-	-	-
Op1O									
<i>Iu</i>	-	-	-	-	-	-	-	-	-
<i>Ip</i>	125s	85s	20 000	-	-	-	-	-	-

7.2.5 Optimisation

The cost variables and the running cost function were included in the virtual model of the conceptual production line. The annual running cost function in this case was used with the initial cost, ξ_I and the delta throughput to cost, $\Delta\xi_T$. Investment alternatives combined with lean buffer configuration are the inputs to control during optimisation. All buffer capacities were subject to optimisation between 1 and 40 entries in steps of 1, except three buffers where one is a conveyor with a size constraint limiting the maximum number of entries to 5 and the other two have a constraint caused by a minimum number of one pallet containing 24 items.

Objectives for optimisation were:

$$\min(\xi_R), \min(\lambda), \min(Bc) \quad (7.2)$$

where ξ_R = Running cost, λ = Investment (Improvement cost) and Bc = Lean buffer capacity.

The NSGA-II algorithm (Deb, 2001) for multi-objective optimisation was used. The optimisation was run with 20 000 simulation iterations, each based on 5 replications, with eight days as the simulation horizon, including one day for warm-up.

7.2.6 Optimisation Results

The result of the optimisation can be plotted forming Pareto fronts with regard to the conflicting objectives of which the most interesting are investment versus running cost, shown in Figure 7.19.

Since there were three objectives in the optimisation, the two-dimensional plot of non-dominated solutions does not reflect the typical two-objective Pareto front appearance.

An interesting conclusion is that the cost performance could be improved from \$4.9M to \$4.4M, only by re-configuring the buffer capacity. That is, $(4.9-4.4)/4.9 = 10\%$ improvement. However, this requires the buffer capacity combinations to be realistic for

implementation. By plotting the throughput versus the total buffer capacity in the line, Figure 7.20, some further interesting properties can be discovered.

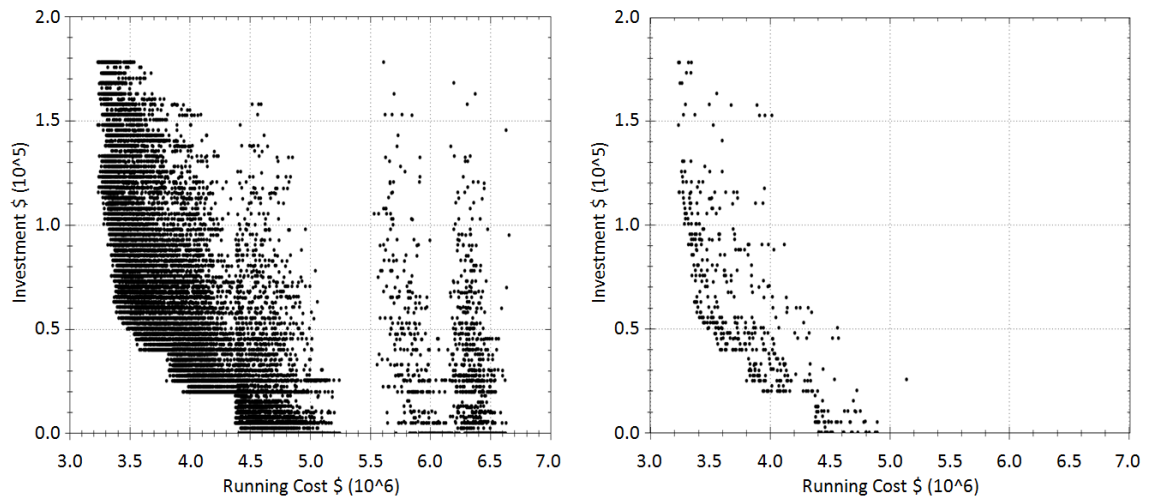


Figure 7.19. Investment vs. running cost, complete data set to the left and only non-dominated solutions to the right.

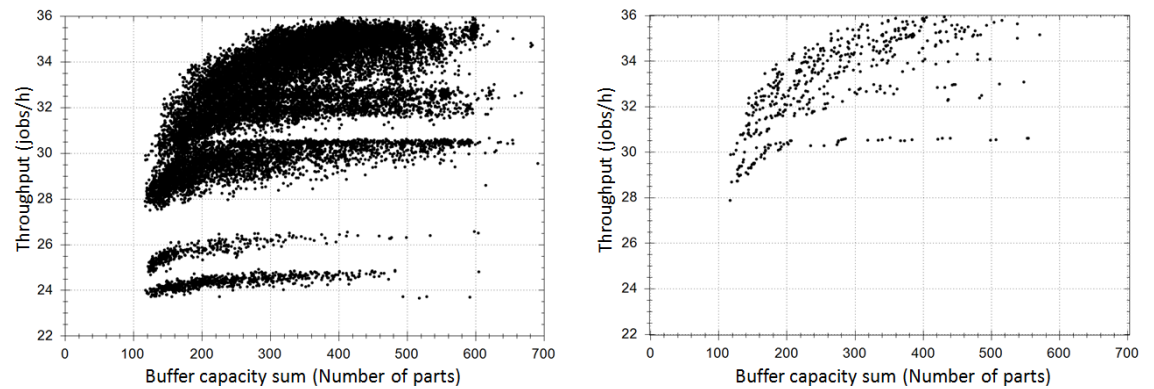


Figure 7.20. Throughput vs. buffer capacity, complete data set to the left and only non-dominated solutions to the right.

The maximum throughput with the suggested changes in the line is approximately 36 JPH and requires a total buffer capacity of 400 entries. The total buffer capacity of the initial line was only 238 entries, limiting the maximum throughput to somewhat over 34

JPH. By running an optimisation with the same improvement and investment parameters without buffer capacity optimisation, this becomes even clearer, as shown in Figure 7.21. The best solutions for throughput just exceed 34 JPH, without buffer optimisation, and the best results with buffer optimisation are very close to 36 JPH. This indicates that the initial line buffer configuration is a capacity constraint which also negatively affects the running cost, when considering the throughput to cost model. Another conclusion is that it is not possible to reach the throughput objective, given the proposed equipment improvements, without re-configuring buffer capacity.

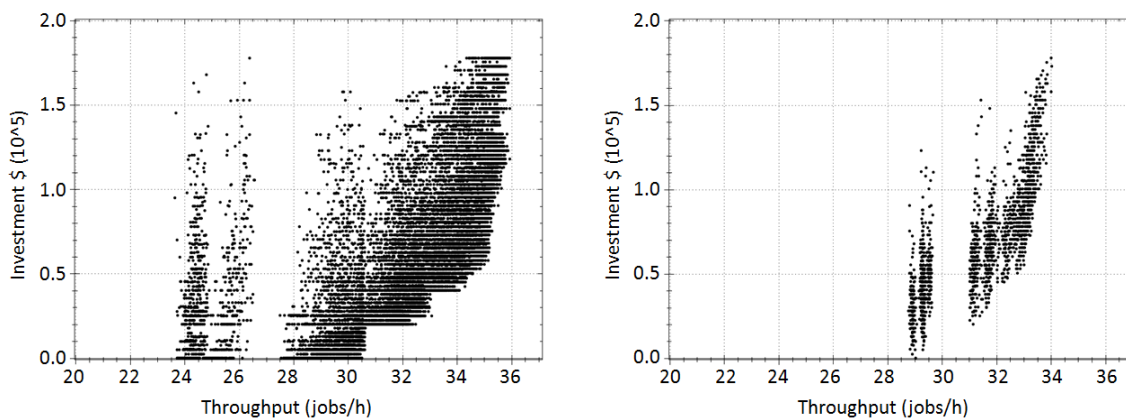


Figure 7.21. Left: Experiment run with buffer capacity optimisation. Right: Experiment run without buffer capacity optimisation.

7.2.7 Post-optimality analysis

In order to find a relevant trade-off between investment and running cost, the data must be analysed with these two objectives in mind. Finding the right solution within 20 000 data records can be difficult. To reduce the effort, some essential objective attributes must be in focus. After a discussion with the production engineers and the line supervisors, it was agreed that the throughput must be at least 34.5, in order to completely remove the need of additional production time.

The first analysis, sorting the data for throughput over 34.5 and minimum investment, shows that theoretically it would be possible to reach the throughput objective with an investment of \$50, 000. After further analysis, it was found that the solution contains major changes in buffer capacity, which would not be feasible to implement in the short term, since more than 400 buffer entries would be required in the line. It was agreed to add a constraint limiting the maximum buffer capacity to 300 and to sort the data accordingly. This resulted in 171 records of the initial 20 000 fulfilling the requirements. The minimum investment among these solutions was \$65, 000, requiring 19 buffers to be increased.

After a discussion with the engineering team, it was decided that implementing these buffer changes was also not feasible in the short term. It was then agreed to search for a solution with as few buffer increases as possible. Following a review of the best solutions with regard to the objectives, a new solution was configured manually, based on the optimisation results. It included 11 buffer increases and a throughput of 34.7 JPH with a standard deviation of 0.13, verified by simulation in the same model used for the optimisation, see Tables 7.8 and 7.9.

Table 7.8. Selected line configuration.

Investments								
<i>Iu</i> Op1E	<i>Ip</i> Op1G	<i>Ip</i> Op1J	<i>Ip</i> Op1N	<i>Ip</i> Op1O	<i>Iu</i> Op1G	<i>Ip</i> Op1H	<i>Iu</i> Op1N	<i>Ip</i> Op1E
2	1	1	1	1	3	1	1	2
Parameter settings								
96%	138,3s	130s	80s	85s	96%	115s	95%	133s
\$7 942	\$20 000	\$20 000	\$20 000	\$20 000	\$32 500	\$2 500	\$5 000	\$20 000
Sum								\$147943

Table 7.9. Selected line configuration simulation results.

Variable	Mean	Std. Dev.
Parts Produced	5831,20	22,64
Throughput	34,71	0,13
Lead Time (complete system cycle time)	17018,44	292,76
WIP	164,78	3,52
S1 - Parts Produced	3578,20	26,09
S1 - Throughput	21,30	0,16
S1 - Lead Time	18520,25	695,74
S2 - Parts Produced	2253,00	12,37
S2 - Throughput	13,41	0,07
S2 - Lead Time	14636,73	384,83

The new buffer configuration derived from one of the optimised solutions was achieved by setting the capacity for a number of buffers to the original values. The selection criteria were to leave buffers that had a larger capacity than the optimised levels unchanged and, at the same time, leave the capacity of buffers with small optimised increases at original values, as shown in Table 7.10.

Despite increasing the buffer capacity, the selected solution actually performs better than the initial line configuration, in terms of WIP, with an average of 165 compared to 188. The investment for this solution is \$150 000 and the annual running cost would be reduced by approximately \$ 1.4M.

Table 7.10. Original, optimised and finally configured buffers.

Buffer Configuration									
B1	B2	B3	B4	B5	B6	B7	B8	B9	
4	30	33	4	5	4	11	26	10	Original
3	6	15	30	14	5	16	10	16	Optimised
4	30	33	30	14	4	16	26	16	Configured
B10	B11	B12	B13	B14	B15	B16	B17	B18	
7	5	2	2	4	4	5	2	2	Original
7	1	2	16	2	15	10	2	2	Optimised
7	5	2	16	4	15	10	2	2	Configured
B19	B20	B21	B22	B23	B24	B25	B26	B27	
3	1	1	1	1	4	4	2	2	Original
4	2	4	3	2	8	1	1	1	Optimised
3	1	4	3	1	8	4	2	2	Configured
B28	B29	B30	B31	Throughput Mean		Total Sum			
5	24	24	4	28,66		236			Original
13	26	25	3	35,20		265			Optimised
13	24	24	4	34,71		329			Configured

After taking into consideration that the shift form which corresponds to the actual time reduction is valid for throughput figures between 26.5 JPH and 34.0 JPH, the real annual saving was recalculated to \$1.3M, by using the throughput to cost function. The delta annual cost and the delta cost due to changed cost per produced unit were set to zero in this case. The estimated performance of the configured solution is calculated in (7.3) to (7.6).

$$\Delta\xi = \Delta\xi_T + \Delta\xi_A + \Delta\xi_U + \Delta\xi_C = \Delta\xi_T + 0 + 0 + 0 = \Delta\xi_T \tag{7.3}$$

$$\Delta \xi_{T_i} = \bar{\xi}_{H_i} \nu_A \left(\frac{1}{\varphi} - \frac{1}{\varphi_{I_i}} \right), \text{ valid for } a_i < \varphi < b_i, \quad 26.5 < \varphi < 34 \quad (7.4)$$

$$\Delta \xi_T = 1450 * 164000 (1/34.0 - 1/28.7) = \$-1.3M \quad (7.5)$$

$$\xi_R = \xi_I + \Delta \xi = 4.9 + (-1.3) = \$3.6M \quad (7.6)$$

The team on the line added 0.5 JPH as a safety precaution when the objective 34.5 was set. The improvement to the throughput performance is $34.7/28.7 = 20.9\%$, the annual cost performance improvement is estimated at $1.3/4.9 = 27\%$, and the cost saving for year one, including investment, is estimated at $(1.3-0.15)/4.9 = 23\%$. The reason that a solution with lower investment was not chosen in this case is the extremely good business case revealed by the optimisation. The opportunity to choose a solution with fewer buffer changes than one of the solutions on the actual Pareto front was convenient for the engineering team carrying out the changes. The resulting line configuration is shown in Figure 7.22.

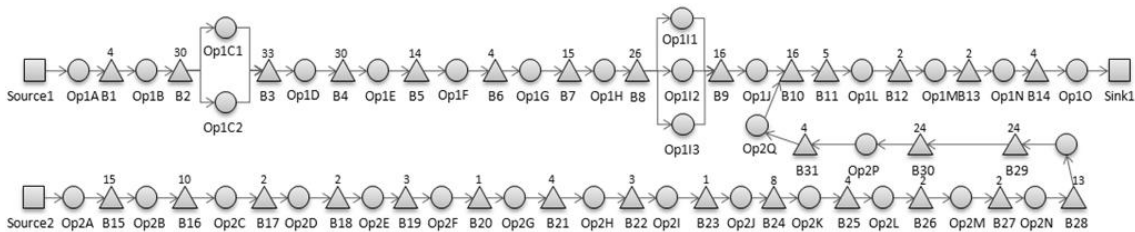


Figure 7.22. Resulting line with re-configured buffer capacity. Allocated buffer capacity is shown in figures above the triangular buffer symbols.

After implementation of the proposed solution, a period of two months was allowed for validation. During this period, the system was operated according to the proposed solution. The throughput was 35.5 JPH, very close to the estimated 34.7 JPH, and the investment rose to \$163, 800, 7% above the estimation of \$147, 943, as shown in Figure 7.23.

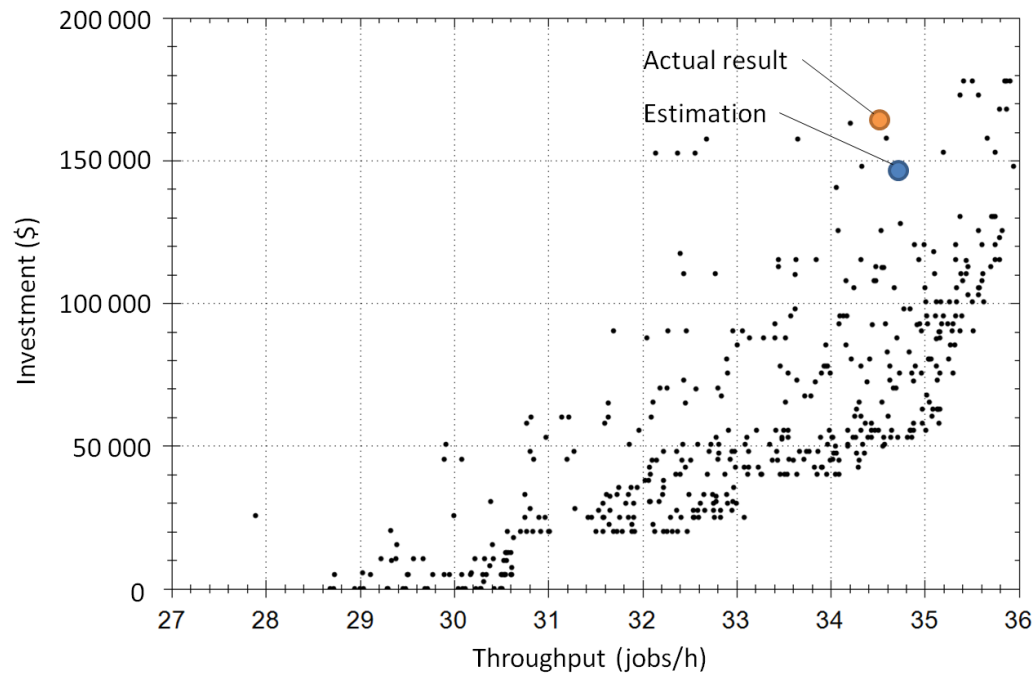


Figure 7.23. Estimated vs. resulting throughput and investment plotted on the non-dominated sorted data set from the optimisation.

The resulting actual running cost was \$3.489M on an annual basis, 3.47% less than the estimated value, \$3.610M. It should be mentioned that the actual production volume was very close to the forecasted volume, deviating just 0.7%, thus offering very good conditions for validation. More detailed figures and additional information from the running cost validation can be found in Appendix 4. The precise extent of the actual saving cannot be established, since it can only be compared to a forecast made in the conceptual phase. Such a forecast contains assumptions very much like those the cost model used during optimisation. For example, the same costs for wages on the different shifts are used both in project forecasting and the cost model connected to the optimisation in this study. It can, however, be established that the estimated running cost was fairly close to the actual resulting running cost.

7.2.8 Knowledge extraction through data mining

For the purpose of further investigating the possibilities of extracting knowledge to be used as an enhancement for decision-making, data mining was applied on the data from the optimisation. Microsoft SQL Server 2005 Data Mining Add-ins for Microsoft Office 2007 was used to perform data analysis that looked for factors favouring high throughput and low running cost. Part of the report from the data mining is shown in Figures 7.24 and 7.25.

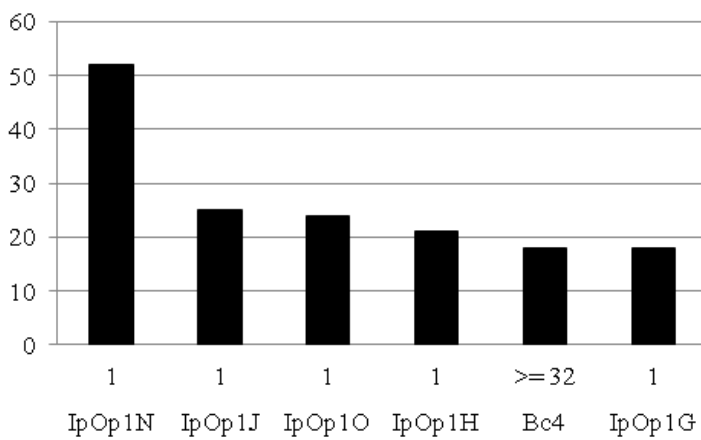


Figure 7.24. Factors favouring high throughput.

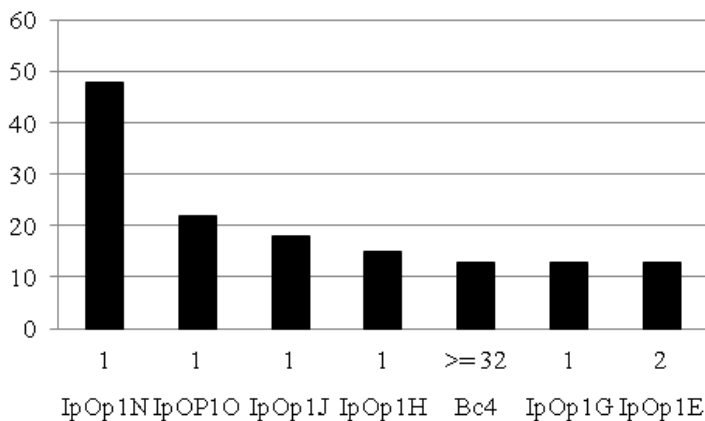


Figure 7.25 Factors favouring low running cost.

The importance of implementing the improvements IpOp1N, IpO1J and IpOp1O can clearly be seen, as well as the significance that the capacity in buffer number 4 is large. Overall, the selected solution reflects the characteristics found in the data mining, indicating that the technique can be useful for providing decision support.

7.2.9 Conclusions

The potential of applying SMO, taking into account financial objectives, such as investment and running cost, for decision-making support in designing/re-configuring production systems, has been explored in this chapter. Evaluating several combined minor improvements with the help of MOO has opened the opportunity to identify a set of solutions revealing significant financial improvement which cannot be sought by applying any current industrial procedures. In the production line studied in this chapter, the throughput could be improved by more than 20% and the cost performance on an annual basis can be improved by more than 25% by applying SMO, including financial objectives. The important results from the SMO study are briefly summarised below:

- One finding by the SMO is that a 10% annual running cost reduction would be achievable by only re-configuring the buffer capacities.
- Given the proposed equipment improvements, it is not possible to reach the target capacity without re-configuring buffer capacity. In other words, investment for improvements and buffer capacities cannot be optimised separately but need to be considered simultaneously.
- By utilising the knowledge created by SMO, a feasible solution, with a very limited need for investments, could be selected in order to improve the throughput by more than 20% and the annual running cost performance by more than 25%. That is, SMO including investment and running cost objectives has proven to be a very promising concept for production system improvement and development.

- WIP could be reduced, despite increased buffer capacity, with regard to a combination of improvements.
- Data mining seems to be a useful tool for finding key influencing factors from SMO, as a support for creating knowledge to be applied within production system design.
- Including cost parameters and cost objectives in SMO enhances the capability of the method as a decision support instrument within the industry.
- In summary, this case study has adequately proven that such a financial-based SMO method can be very valuable for practical industrial applications.

7.3 Automatic bottleneck detection and identification of improvement potentials using multi-objective optimisation and post-optimality analysis

In this section the SCORE-analysis method, proposed in Chapter 6, for the detection and ranking of constraints and bottlenecks, is applied on a real industrial problem for verification.

7.3.1 Background

Due to a shortage of capacity in an advanced production line for automotive components, it was necessary to improve the throughput performance. The production system included a combination of serial and parallel equipment, transfers, and cell automation. Due to strict quality demands in combination with advanced materials, a number of feedback loops for rework is part of the line. A simulation model of the line was built and validated, in order to conduct an analysis using the shifting bottleneck detection technique. The bottleneck analysis indicated that M17 would be the constraint of the system, as seen in Figure 7.26.

To verify the results, a simulation with reduced cycle time, from 40.1s to 30s, in M17 was run, which revealed somewhat unexpected results. The system did not improve and throughput performance may actually have deteriorated. The deterioration was not significant enough to be absolutely statistically proven, but the system definitely did not improve, as throughput went from 50.1 parts per hour down to 48.4 parts per hour. Simultaneously, the lead time (complete system cycle time) increased from 36 hours and 43 minutes to 37 hours and 50 minutes. A new shifting bottleneck analysis was run and the results, after reduction of cycle time in M17, are shown in Figure 7.27. According to the analysis, M17 was no longer the bottleneck of the system, but the performance did not improve and might actually become worse.

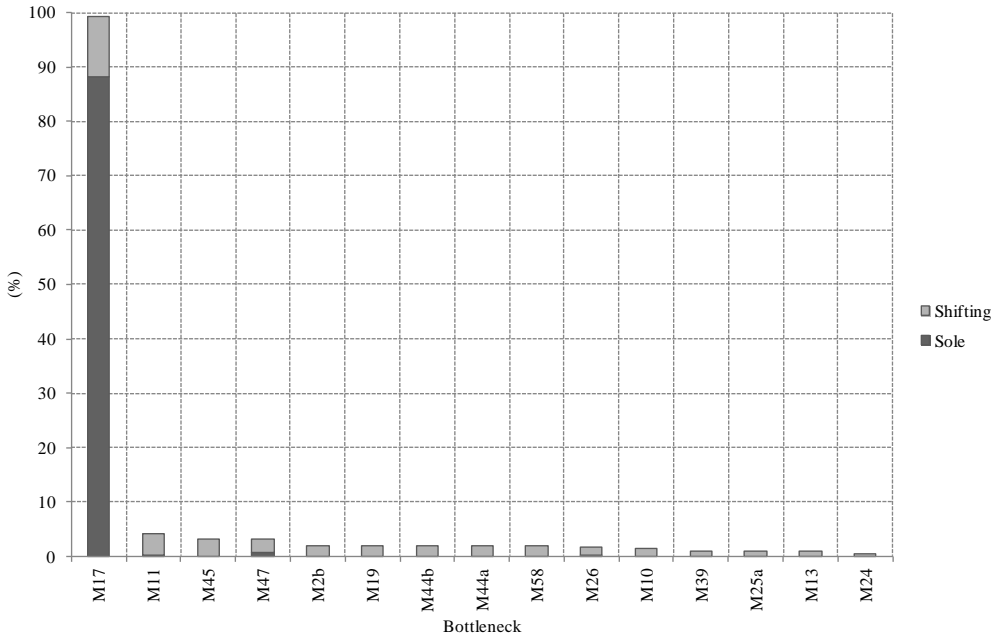


Figure 7.26. Initial shifting bottleneck detection analysis.

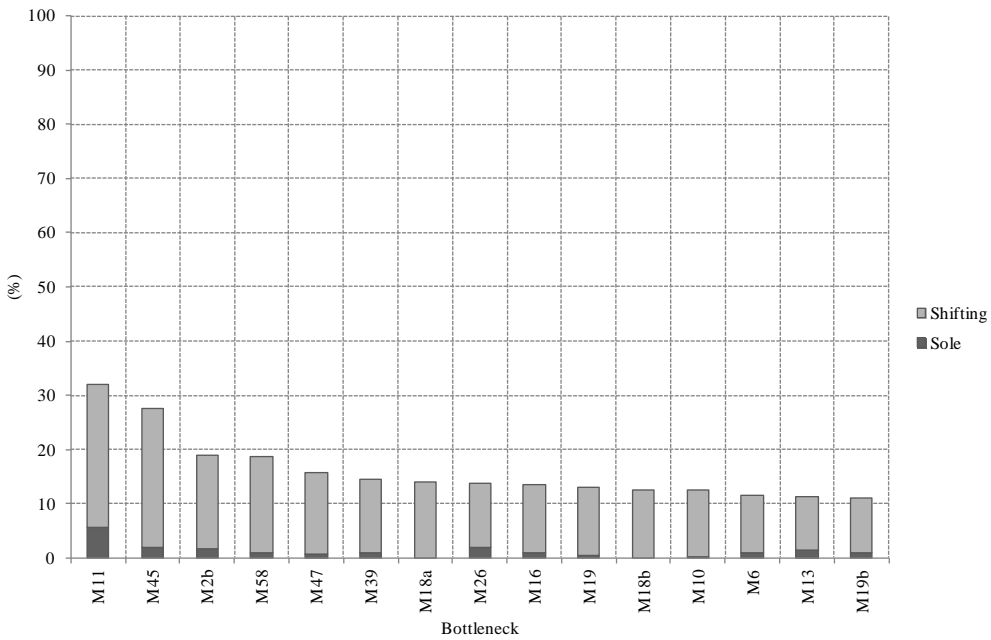


Figure 7.27. Shifting bottleneck detection analysis after the cycle time reduction in M17.

How can this be explained? There are actually other examples in literature (Ignizio, 2009) showing this kind of effect on a production system's performance as a result of local improvements. What about the analysis method? Could there be other alternative methods to analyse the system and search for improvement opportunities? Let us apply the novel SCORE-analysis method and see if we can find out more about the system and gain knowledge to explain the shifting bottleneck results.

7.3.2 Application of the SCORE method

The simulation model was prepared to handle the two level constraint removal parameters according to equations (7.7) to (7.9).

$$\hat{\alpha}_i = \alpha_i \cdot 0.7 \text{ (s)} \quad (7.7)$$

$$\hat{\beta}_i = 99 \quad (\%) \quad (7.8)$$

$$\hat{\gamma}_i = \gamma_i \cdot x \text{ (s)} \quad (7.9)$$

where: x = reduced MDT percentage.

An optimisation with minimisation of the number of changes and maximisation of throughput was run for 30 000 iterations and 5 replications, using the NSGA-II algorithm with meta-modelling enhancement. Frequency analysis with Pareto charting was performed on the resulting complete data set shown in Figure 7.28 and the rank one (non-dominated) solutions illustrated in Figure 7.29.

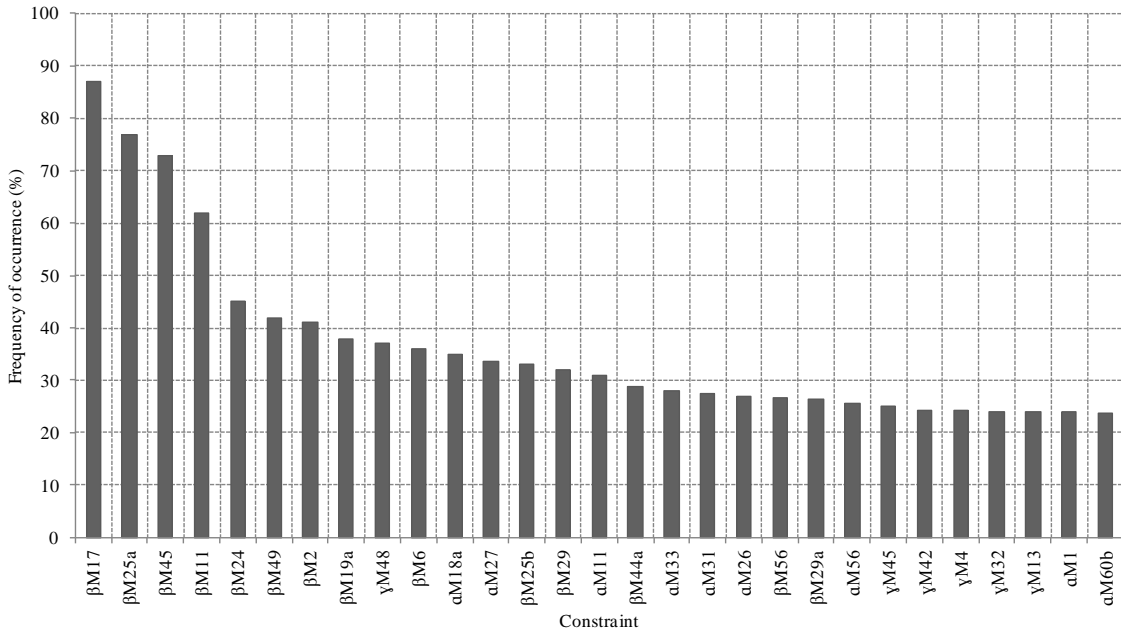


Figure 7.28. SCORE-analysis results from rank one (non-dominated) solutions.

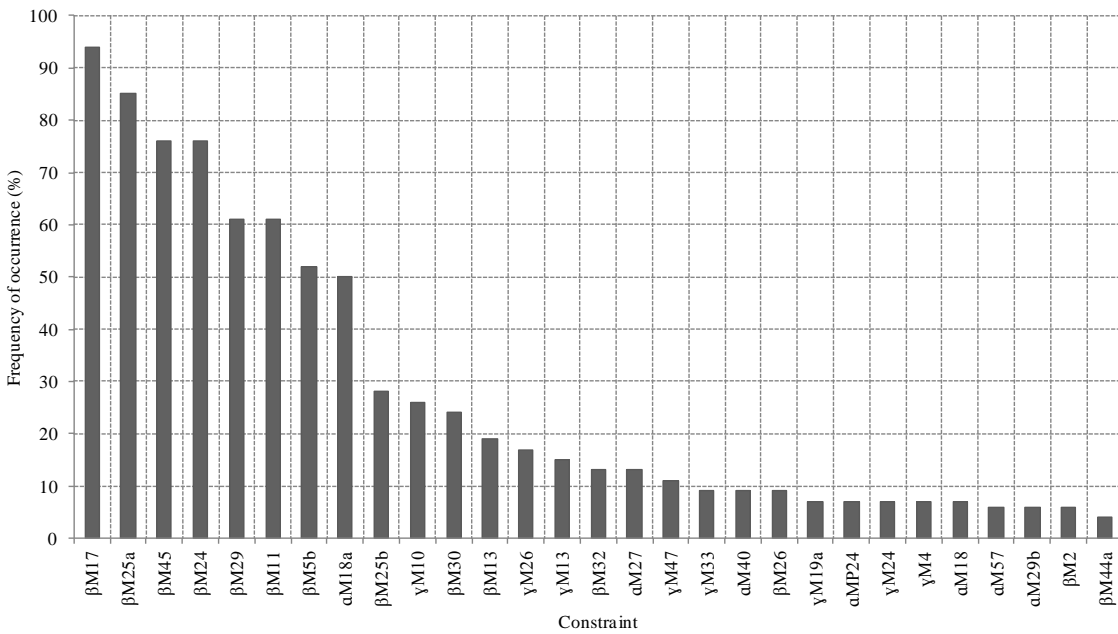


Figure 7.29. SCORE-analysis results from a complete data set.

The SCORE-analysis reveals useful information and knowledge about the system that might help us explain why the improvement of the cycle time in M17 did not improve the system. The SCORE-analysis also pinpoints M17 as the main constraint of the system. However, it also tells us that it is the availability in M17 that is the main problem. Hence, improving the cycle time in M17 is the wrong action to take. The shifting bottleneck detection technique actually found the right place to improve, but it could not tell us what type of action is necessary. This also reveals one of the strengths of the SCORE-analysis method, the ability to indicate the type of action required.

A prediction of the effect on the production system can be done by simulating the suggested improvements, in order of importance. Plotted as accumulated changes in Figure 7.30, the improvements applied in order to have considerable effect on the throughput performance and, in this case, the first eight improvements have a positive effect on the system.

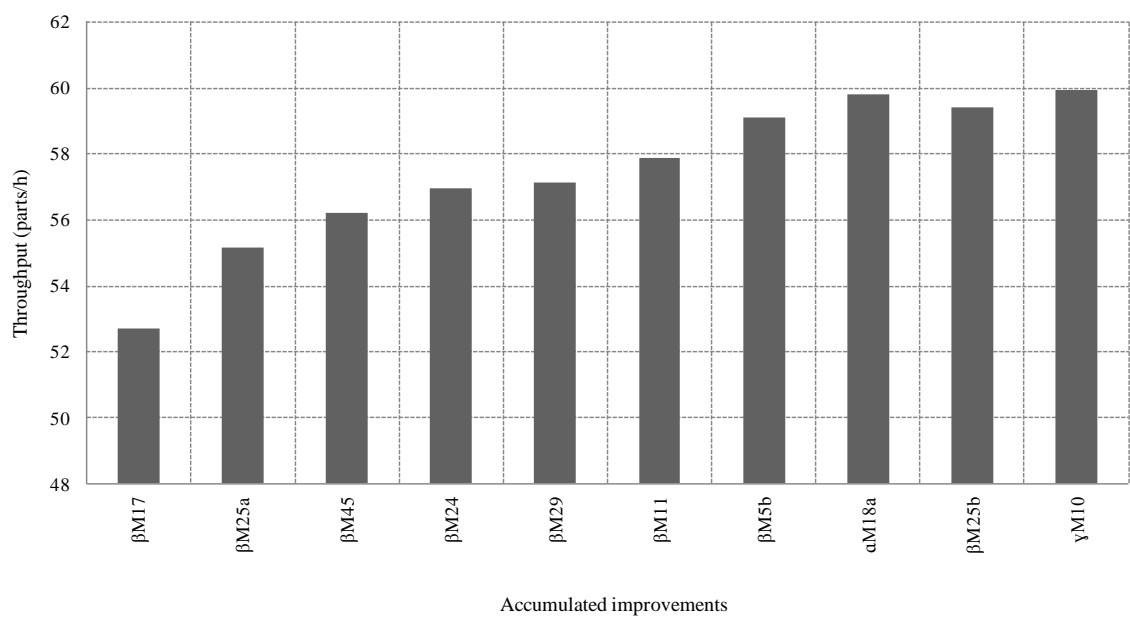


Figure 7.30. Simulated effect on throughput from improvements suggested by the SCORE-analysis.

There are still some answers to be found. We do not know how much the availability in M17 needs to be improved or if there are any dependencies among the possible improvements. By running the top ten constraints, selected as in Figure 7.31, in a new optimisation with narrow steps in parameter values, we can decipher more information. The results from the new optimisation run can be analysed in various ways by sorting and plotting, in order to create decision support. An interesting analysis is to search for clusters and dependencies in the data. Figure 7.32 illustrates the effects on throughput from considering dependencies or clusters among the constraints.

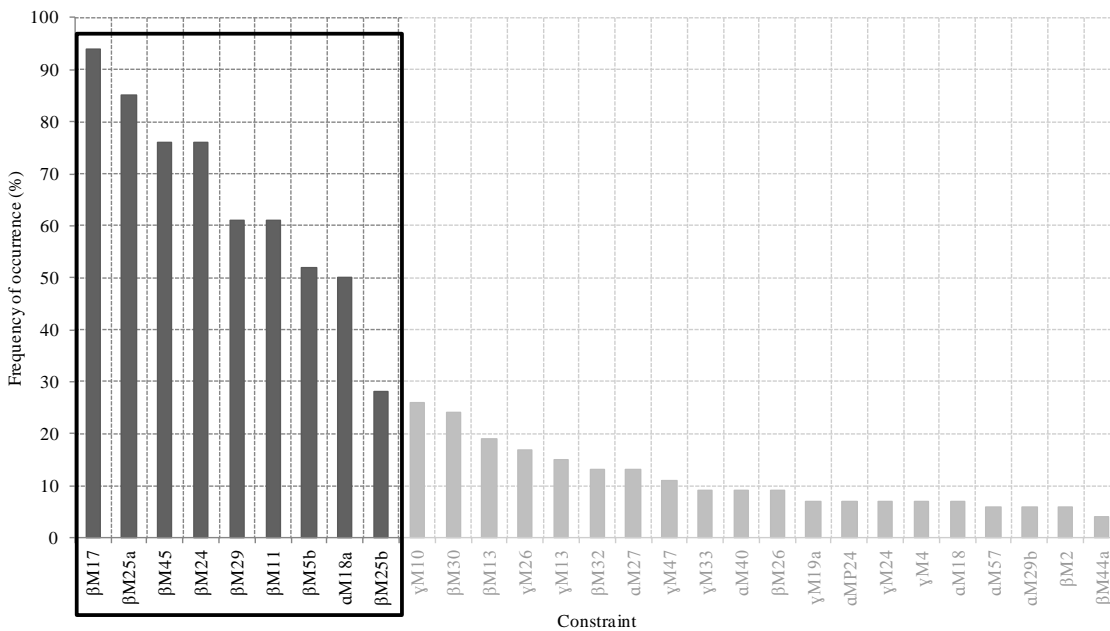


Figure 7.31. Selected constraints for deeper analysis.

The throughput varies from approximately 50 parts per hour to slightly above 60 parts per hour, when all solutions are considered. When solutions that contain improvement of the availability in M17 are filtered out, throughput starts at approximately 51 parts per hour. However, by combining improvement of availability in M17 and M25a, the results in throughput start at about 55 parts per hour. That is, an approximately 10 % improvement opportunity is revealed by combining two actions against constraints. By also improving the availability in M24, another step that increases throughput to over 56

parts per hour can be taken. That is, this kind of analysis can reveal important information about the system, which is valuable for decision-making. Nevertheless, more information can be revealed about the system.

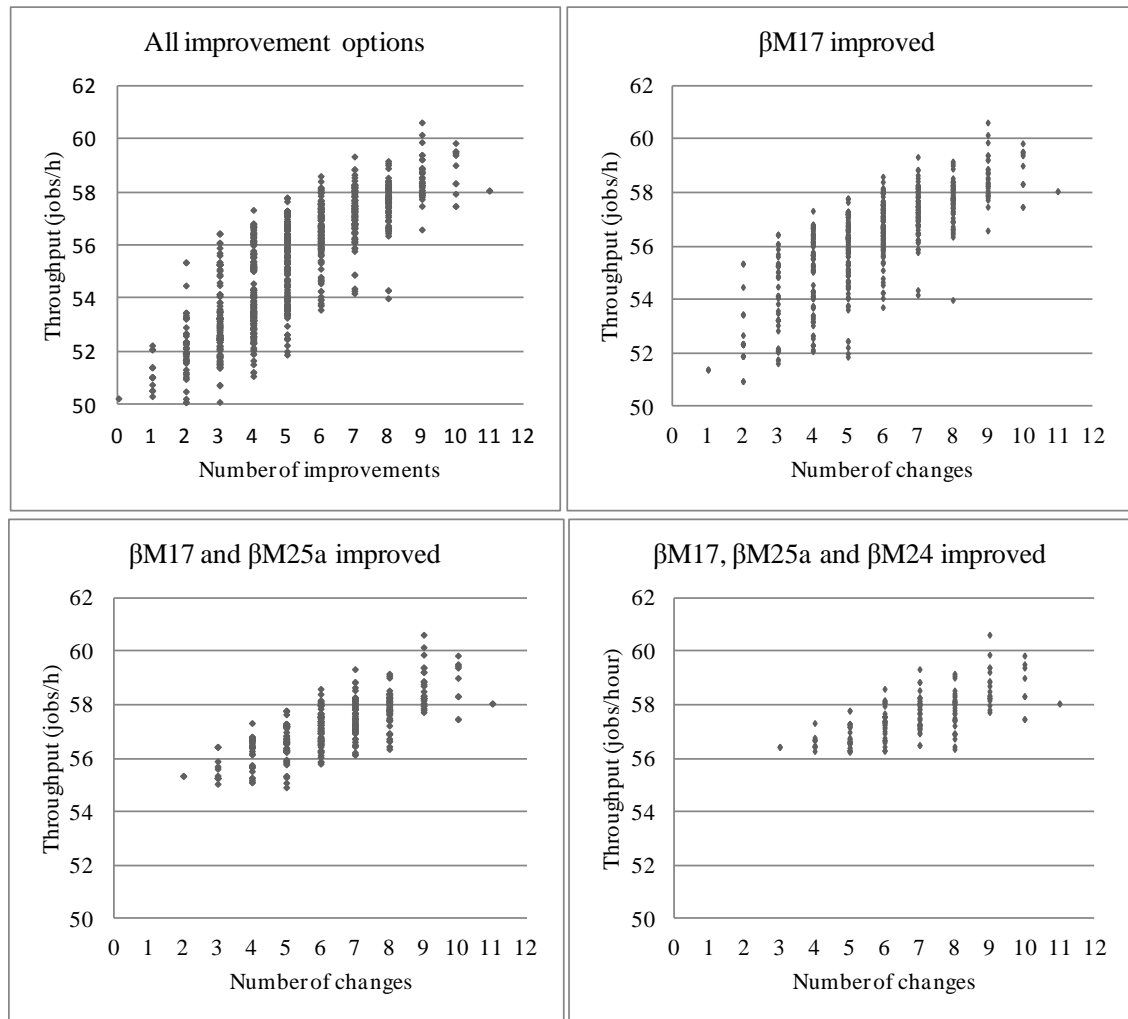


Figure 7.32. Constraint clusters and the effect of combined parameter improvements.

The results from the new optimisation are then subjected to several more sorting processes. Instead of directly using the minimised number of changes, the number of changed operations is calculated for each solution. By sorting out the solutions with the fewest number of changed operations and then searching for the solutions with the

highest throughput, we can compile a decision-support matrix with information on target levels or how much change is required in order to reach a certain throughput, see Table 7.11. Iteration 1 is a simulation of the original line configuration.

Table 7.11. Target levels required to reach a certain throughput.

Iteration	No of Changes	ϕ	Stdev(ϕ)	β_{M17}	β_{M25}	β_{M24}	β_{M45}	β_{M29}	β_{M11}	β_{M5b}	α_{M18a}	β_{M25b}
9725	46	57.61607	1.755041	87	97	96	96	86	88	90	96	88
6268	43	57.48552	2.126498	86	96	96	95	84	89	90	96	89
2660	41	57.075	1.798859	87	88	96	97	83	86	93	96	93
2136	30	55.79861	1.984932	86	87	95	93	87	84	90	96	90
5595	20	55.02976	1.791977	83	89	97	90	82	84	89	96	88
5785	17	54.80456	1.544888	81	88	94	90	82	85	90	96	89
8705	14	54.37897	1.343082	82	85	95	90	83	83	90	96	88
1	0	49.62639	1.743704	81	83	88	90	82	83	89	98	88

Another way to further analyse the system is to use the cost model proposed in Chapter 4. When running an optimisation with, e.g., the investment function, according to (7.10), another decision-support matrix showing available trade-offs between performance and investment or improvement cost can be compiled, as shown in Figure 7.33.

$$\lambda = \sum_{i=1}^m \lambda_{\alpha_i} + \sum_{j=1}^n \lambda_{\beta_j} + \sum_{j=1}^n \lambda_{\gamma_j} + \sum_{k=1}^o \lambda_{B_k} + \lambda_C \quad (7.10)$$

where: λ = Total investment (improvement cost), λ_{α} = Processing time related investment, λ_{β} = Uptime related investment, λ_{γ} = MDT related investment λ_{β} = Buffer capacity related investment and λ_C = Custom investment component.

The combination of the type of information shown by this method provides the decision maker within manufacturing or manufacturing development with opportunities to accurately pinpoint actions and prioritise between conflicting objectives, at a level not previously available.

Decision support matrix										
Iteration	Throughput		Ranked investments							Total inv.
	φ	Stdev (φ)	$\lambda_{\beta}M17$	$\lambda_{\beta}M25a$	$\lambda_{\beta}M24$	$\lambda_{\beta}M45$	$\lambda_{\beta}M11$	$\lambda_{\beta}M10$	$\lambda_{\alpha}M18a$	λ
1	50.60111	0.996934								0
488	51.70056	0.592704		32100					2000	34100
352	52.01111	0.749213		13375	20062	13375				46812
569	52.235	1.256617		32100	20062				2000	54162
839	52.44056	0.398451	40125		20062	13375			2000	75562
1244	52.56806	0.618166	40125	32100		13375			2000	87600
1109	52.84944	1.046442	40125	13375	20062	32100			2000	107662
1247	53.20694	0.780979	40125	32100		13375		26750	2000	114350
1328	53.34694	0.716938	40125	32100	20062	13375		26750	2000	134412
1433	53.71806	0.900604	40125	32100	48150	32100			2000	154475
1370	53.965	0.533821	40125	32100	20062	32100	48150		2000	174537
2162	54.07139	0.630628	96300	32100	48150	32100			2000	210650
2170	54.24639	0.355144	96300	32100	48150	32100	20062			228712

Figure 7.33. Decision-support matrix considering investment.

After the case study, some of the suggested improvements were implemented in the real industrial line, which provided an opportunity to observe the effect of at least the two most significant ones, $\beta M17$ and $\beta M25$. The $\beta M25$ -improvement was actually implemented somewhat differently than expected. Instead of improving the actual machine $\beta M25$, a parallel machine was fitted for batch changes, in order to take some of the work from $\beta M25$. The effect that these two changes resulted in was a throughput increase of approximately five JPH, as expected. However, several other activities were being carried out and an absolutely positive quantitative validation could not be established. From a qualitative perspective, there is a strong indication that the method is working as expected.

7.3.3 A summary of the key findings

The SCORE analysis method has been applied on a real industrial problem and revealed relevant improvement strategies that have the advantage of indicating the type of constraint. The most important findings, in summary:

- There is a potential to combine the SCORE method with cost optimisation, in order to generate improvement strategies that take monetary aspects into account and not just constraints or bottlenecks. When applied within the framework for production systems decision support, the method can provide information on the most beneficial solutions from a cost perspective.
- In summary, the results demonstrate the potential to create a method that provides a new level of information for the support of manufacturing management decisions.
- Sometimes it is essential to consider several constraints in order to gain any significant improvement.

7.4 Post-experimental analysis, post-optimality analysis, and knowledge extraction

Visualisation and the extraction of knowledge from data are essential ingredients in the design of a framework to support decision-making. Innovation through optimisation or the concept of knowledge discovery through post-optimality analysis of MOO was proposed as “Innovization” by Deb and Srinivasan (2006). Knowledge is considered to be rules, principles, and strategies that can explain the key influencing decision variables related to the objectives. Innovization is originally based on post-optimality analysis and the extraction of knowledge from Pareto-optimal solutions (Bandaru and Deb 2010). This provides knowledge about attributes of the system connected to the high performing solutions at the Pareto front. There is, however, one drawback with this concept; the limited ability to find knowledge about parameter settings, strategies, or design principles to avoid, due to the inherent properties of the optimisation procedures to promote and find high performing solutions. This might also be an unwanted restriction in the process of narrowing down optimisation problems by applying rules as constraints or limiters for ranges of parameters.

The concept of SBI, presented by Ng et al., (2009) and Dudas et al., (2011), uses an automatic procedure to extract data from SBO. Instead of just performing post-optimality analysis on the set of Pareto-optimal solutions, as proposed by Bandaru and Deb (2010), the entire data set from optimisation is analysed, enabling the discovery of attributes that distinguish high performing Pareto-optimal from non-Pareto-optimal solutions.

Furthermore, the concept of interleaving MOO and knowledge discovery for production systems was presented by Ng et al., (2012). Initially, a first rough discovery of the objective space is conducted through an optimisation or some other search method. Then the data is analysed and examined for rules or design principles relating decision variables to the objectives. The rules best matching the decision maker’s preferences can be taken into account and applied in a sequential re-defined optimisation round.

With a set of rules narrowing the optimisation problem down, the computational resources required to solve the problem might be reduced. Another approach to reduce the required computational efforts and to focus optimisations is to use algorithms that have the ability to focus on a certain area or a direction in the objective space. One example of such a specialised algorithm applied on an experiment with the SCORE method (proposed in Chapter 6) has been presented by Siegmund et al., (2012).

This study is related to the development of the methodology for knowledge discovery by interleaving MOO and data mining presented by Ng et al., (2012) and aimed at investigating whether the most essential rules and some basic knowledge about the system can already be revealed by the first rough discovery of the objective space. The objectives are to find out whether the combined use of a random search method with data mining and MOO has the potential to enhance the resulting decision-making prerequisites and, at the same time, reduce the amount of computational resources required.

7.4.1 Experiments

Optimisation methods that will promote solutions which best satisfy the problems' objectives and the discovery of knowledge about settings to avoid, in a high performing system, would require some alternative search method. In the following study, LHS design was used because it has random search abilities that do not repeat the same solution twice. The idea is that knowledge gained by such a study, hopefully revealing a wider set of rules, can then be used either directly as decision support or as input for a more precisely targeted optimisation. Instead of post-optimality analysis, this concept could be referred to as *post-experimental analysis*.

An application study with industrial experiments, related to production systems design and improvement, was earlier presented in Chapter 7 (section 7.2) and published by Pehrsson et al., (2011). Extended analysis on the optimised data from the experiments has been conducted by both Dudas et al., (2012) and Ng et al., (2012). A production line

suffering from high running cost and capacity constraints was the subject for an industrial improvement project. A number of improvements or investments, in terms of increased availability and reduced processing times in some of the workstations, were believed to enable higher throughput and reduce running cost. The main objectives of the optimisation study were to reduce running cost with minimal investments while keeping the inter-workstation buffers at acceptable levels. FACTS Analyzer (Ng et al. 2007) was used to develop a simulation model of the production line, as shown in Figure 7.34, with labelled workstations and inter-workstation buffers. Before the optimisation study, the model was validated to correspond with the throughput of the real line.

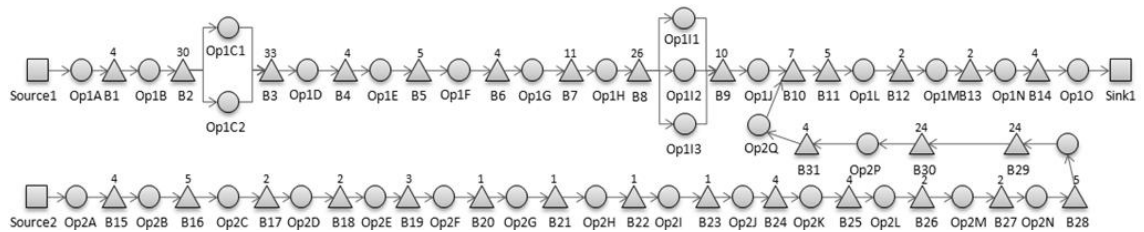


Figure 7.34. Simulation model of the production line.

The three optimisation objectives were to minimise running cost, minimise investment (improvement) cost and minimise lean buffer capacity according to the formulas (7.11) to (7.13) based on the cost modelling technique proposed in Chapter 4.

$$\min(\xi_R = \xi_I + \sum_{i=1}^m \Delta \xi_{T_i}) \quad (7.11)$$

$$\min(\lambda = \sum_{i=1}^m \lambda_{\alpha_i} + \sum_{j=1}^n \lambda_{\beta_j}) \quad (7.12)$$

$$\min(Bc = \sum_{i=1}^m Bc_i) \quad (7.13)$$

A LHS study was performed before the actual optimisation study began and the resulting data was analysed after 1000 iterations and 2000 iterations. In this case, visual

tools for post-optimality analysis were used to find knowledge about important parameter settings and design principles.

7.4.2 Knowledge extraction through visual data mining

The automated innovization methods introduced by Bandaru and Deb (2010) do not provide the opportunity to search for rules of the type smaller than, or larger than, and do not work properly with discrete variables, due to the fact that each parameter step can be seen as a separate cluster. Analysis through decision trees is one way of extracting such rules and has been tested by Dudas et al., (2011) on the results from the experiments presented in Chapter 7 (Section 7.2.). However, when relating the problem to an industrial decision-maker's requirements, it would be desirable to use a method that is easy to understand and trust. In an attempt to fulfil the desired properties, a visual rule extraction technique for discrete variables that has the potential to be automated is proposed. It is also applied in Chapter 4 (Section 4.5). By searching for step effects in parameter values related to an objective, some essential information about relations between parameter settings and objectives can be found. The principle for the visual rule extraction proposed can be seen in Figure 7.35.

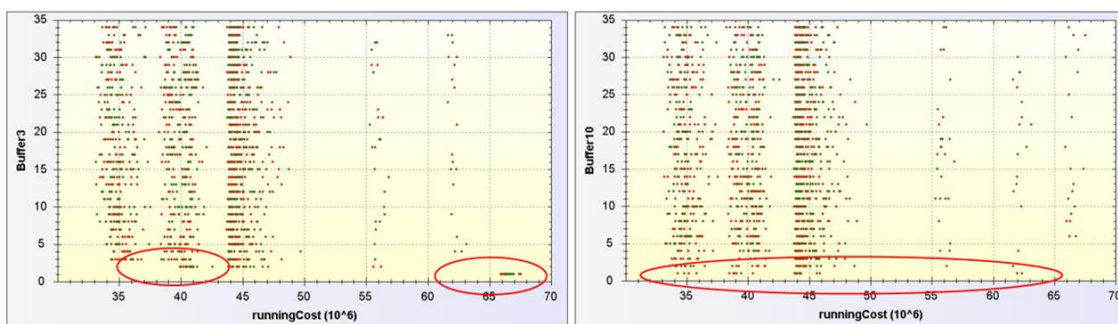


Figure 7.35. To the left: A parameter with step effects (rules). To the right: A parameter without step effects (rules).

In theory, rules concerning parameters that are more of the type true or false, 1 or 0, or a generally narrower parameter range will have a higher probability of detection, due to a

higher probability of occurrence in the results from a random experiment. First, all input parameters were analysed with regard to the running cost objective, on the basis of 1000 iterations LHS. The parameters identified as containing rules in relation to the running cost objective can be seen in Figure 7.36.

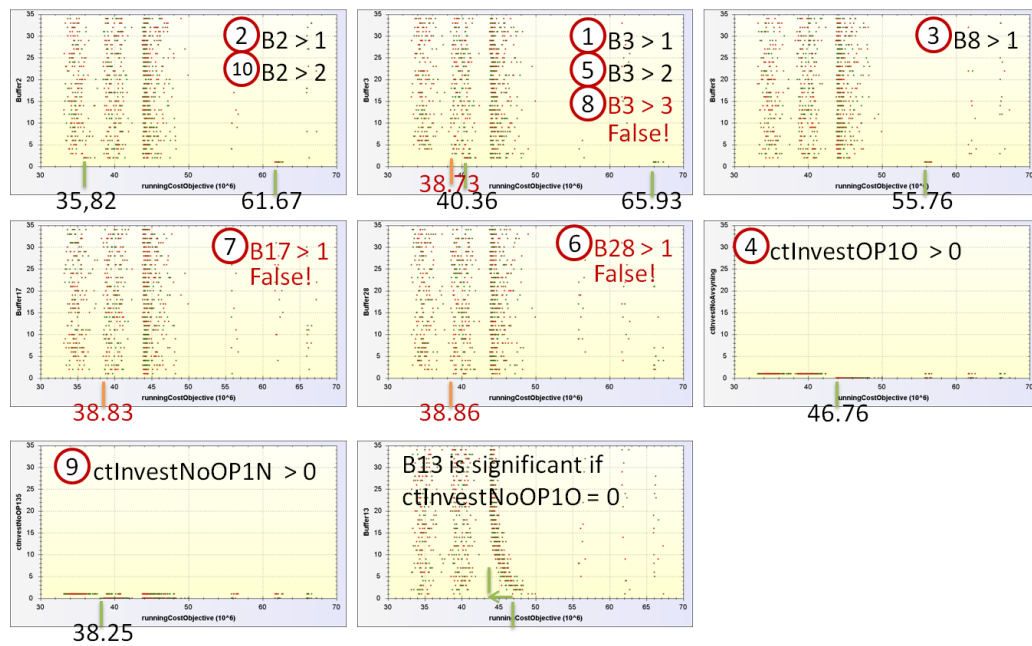


Figure 7.36. Rule extraction from 1000 iterations LHS with some false rules detected, numbered in order of contribution to improvement in the running cost objective.

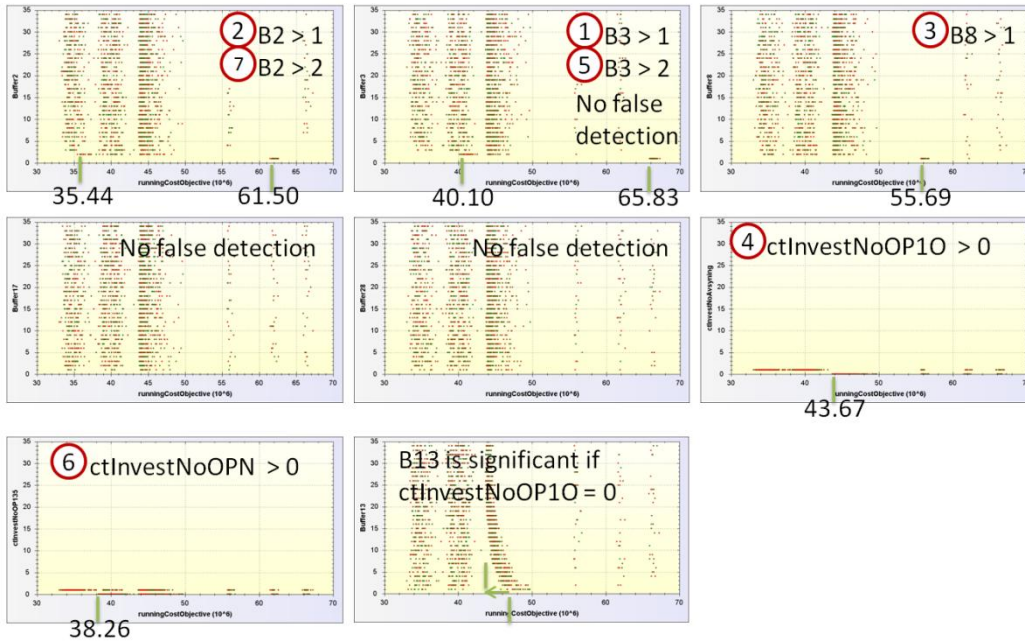


Figure 7.37. Rule extraction from 2000 iterations LHS, numbered in order of contribution to improvement in the running cost objective.

From only 1000 iterations, some false rules were discovered, which can be seen in the comparison with the results from 2000 iterations, shown in Figure 7.37. The results were also compared with an earlier study (Dudas et al., 2012) based on the results from a data set generated by a complete MOO, according to Figure 7.38. The results from that study, shown in Table 7.12, were generated through a top-level decision tree analysis of the complete solution set from an optimisation. All rules discovered by the top-level decision tree analysis could be found using the proposed visual analysis method. The proposed visual method applied on the data from the LHS experiment could still reveal some other rules that would be essential to avoid when creating high performing solutions. The first is that $B3=1$ leads to even worse solutions than the ones revealed in the original optimisation study. It can be seen as another cluster or region in the data from the LHS experiments in Figure 7.39. The second new rule $B3>2$ is essential for achieving the best solutions within region 2 or to reach region 1. The third rule discovered is that $B2>2$ is required to achieve the lowest running costs within

region 1. The second and third rules are not very prominent and some further analysis might be required to ensure that they are correct. With the rules applied and plotted with colour coding on the complete results from the optimisation (Figure 7.40), it can be seen that no solutions close to the Pareto frontier contain the parameter values that need to be avoided. Hence, the rules seem to be valid. The proposed visual rule extraction technique will only work with discrete parameters. However, it might be viable to transfer continuous parameters into discrete ones, in some situations. The visual rule extraction technique has some potential to be automated through comparison of the effect on the objectives by going from one parameter value to the next. The size of a step that is required to be considered a subject for rule extraction could be controlled with the introduction of a sensitivity operator.

Table 7.12. Results from a top-level decision tree analysis (Dudas et al. 2013).

Region	Rule
1	$(B_2 \ \& \ B_8) > 1 \ \& \ I_{p_{OP10}} \neq 0 \ \& \ I_{p_{OP1N}} \neq 0$
2	$(B_2 \ \& \ B_8) > 1 \ \& \ I_{p_{OP10}} \neq 0 \ \& \ I_{p_{OP1N}} = 0$
3	$(B_2 \ \& \ B_8) > 1 \ \& \ I_{p_{OP10}} = 0$
4	$B_2 > 1 \ \& \ B_8 = 1$
5	$B_2 = 1$

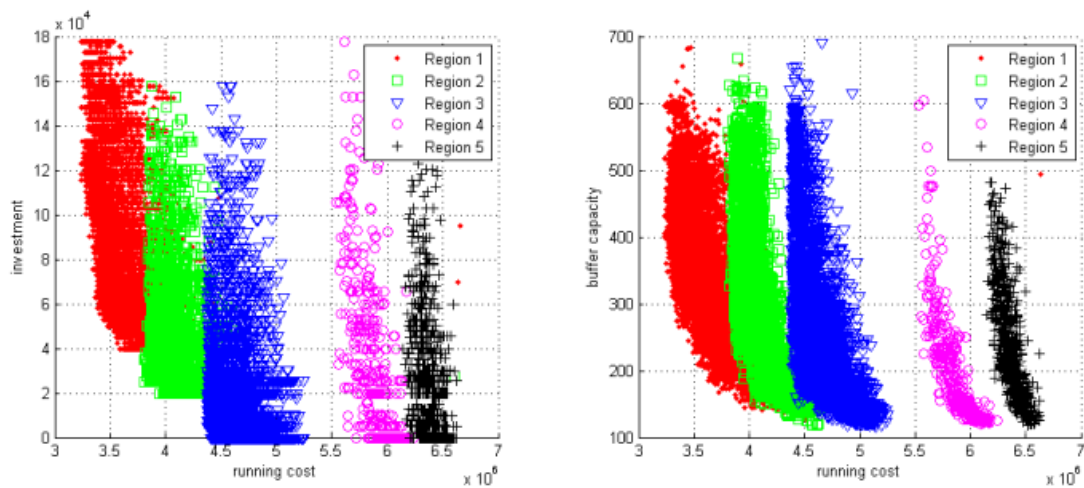


Figure 7.38. Colour-coded visualisation of the rules separating the objective space based on decision tree analysis (Dudas et al. 2013).

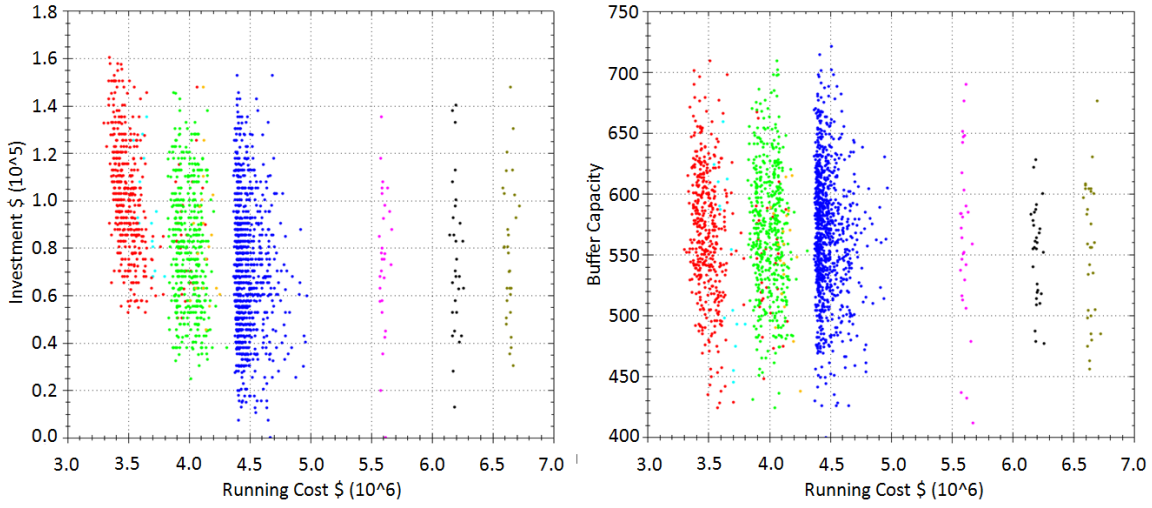


Figure 7.39. Colour-coded visualisation of the rules extracted from Latin hyper cube experiment.

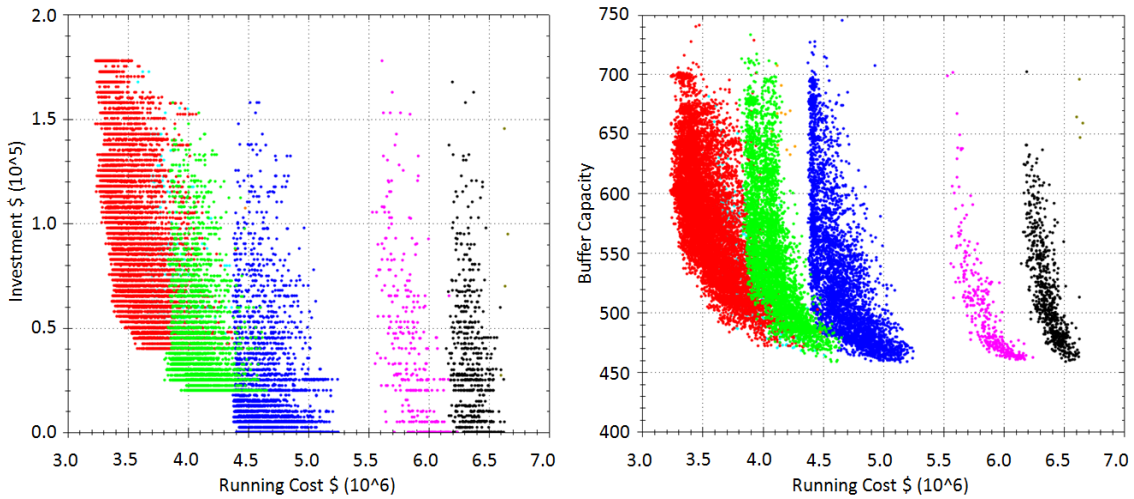


Figure 7.40. Extracted rules from the Latin hyper cube experiment applied with colour-coding on data from the original optimisation of the system.

7.4.3 Optimisation with rules

The results from the rule extraction were used to set up a new optimisation with the required rules applied to achieve the cluster with the lowest running cost. The same NSGA-II algorithm was used with the identical settings employed for the original experiment, but with the reduced number of 5000 iterations instead of the original 20,000. The total number of iterations together with the initial 2000 iterations of the LHS experiment was 7000 or 35% of the original computational budget. The new results are shown in Figure 7.41.

The application of the rules during optimisation results in a well-defined cluster, corresponding to the most favourable area of the original optimisation, mapped by the rules. In order to be able to compare the two results from an optimisation efficiency perspective, the two data sets were combined and filtered for non-dominated solutions. The result can be seen in Figure 7.42.

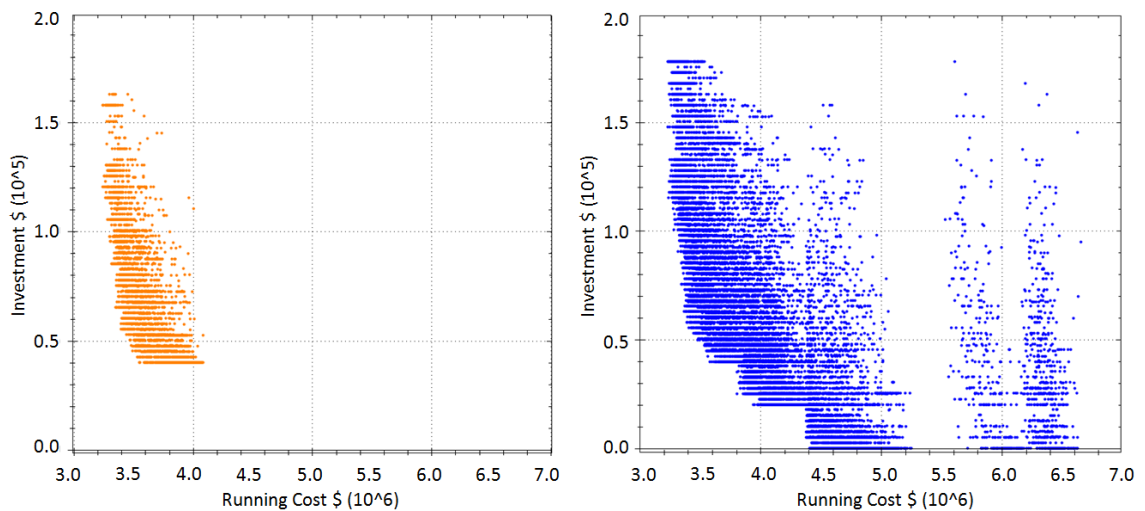


Figure 7.41. Left: Result from 5 000 iterations optimisation with rules applied. Right: Result from 20 000 iterations optimisation without rules applied.

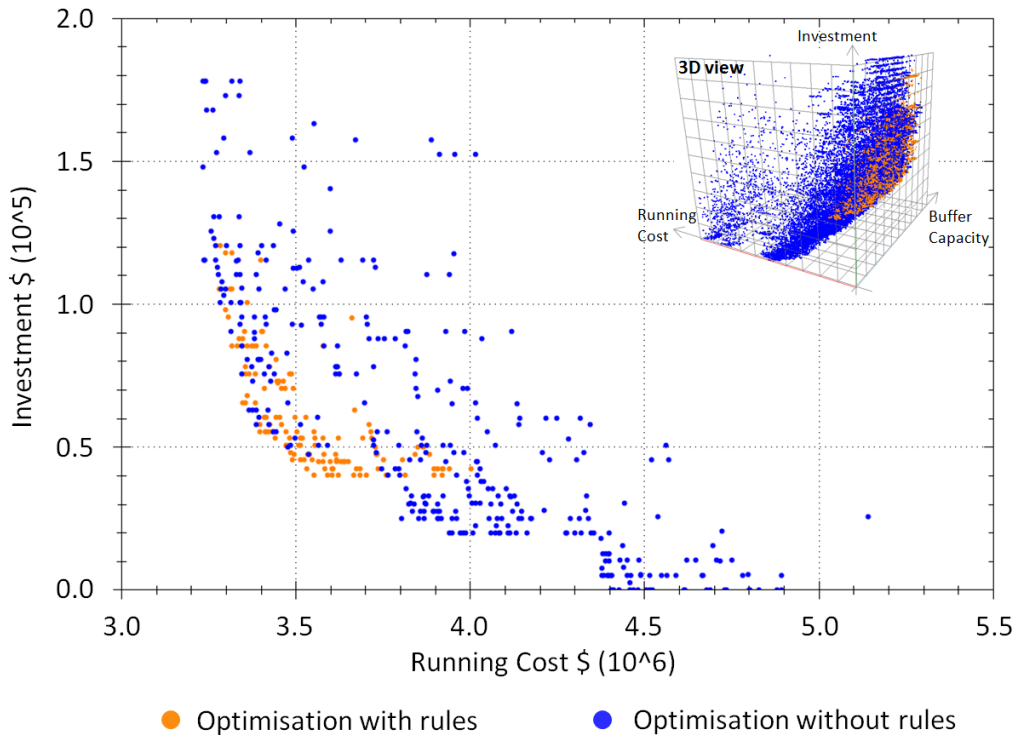


Figure 7.42. Non-dominated solutions in the combined data sets from optimisation with rules (orange) and optimisation without rules (blue). Upper right: Complete combined data sets.

The application of rules during optimisation not only reduces the computational efforts. It also enables somewhat better solutions to be found in an interesting area close to a knee-point approximately \$400,000 investment and M\$3.5 to M\$3.6 running cost.

7.4.4 Comparison with SCORE analysis

The Simulation-based Constraints Removal (SCORE) method for bottleneck detection, proposed in Chapter 6, does not take cost aspects or opportunities with buffer changes into account in its original form. However, the main constraints of a line are closely linked to the throughput performance of the system and the running cost calculation is to a large extent dependent on throughput. Hence, the main constraints of the line should have some relation to the results from the cost optimisation study, as long as the

required investment is reasonable. The simulation model from the cost optimisation presented in Chapter 4 was the subject for a SCORE analysis and the results can be seen in Figure 7.43.

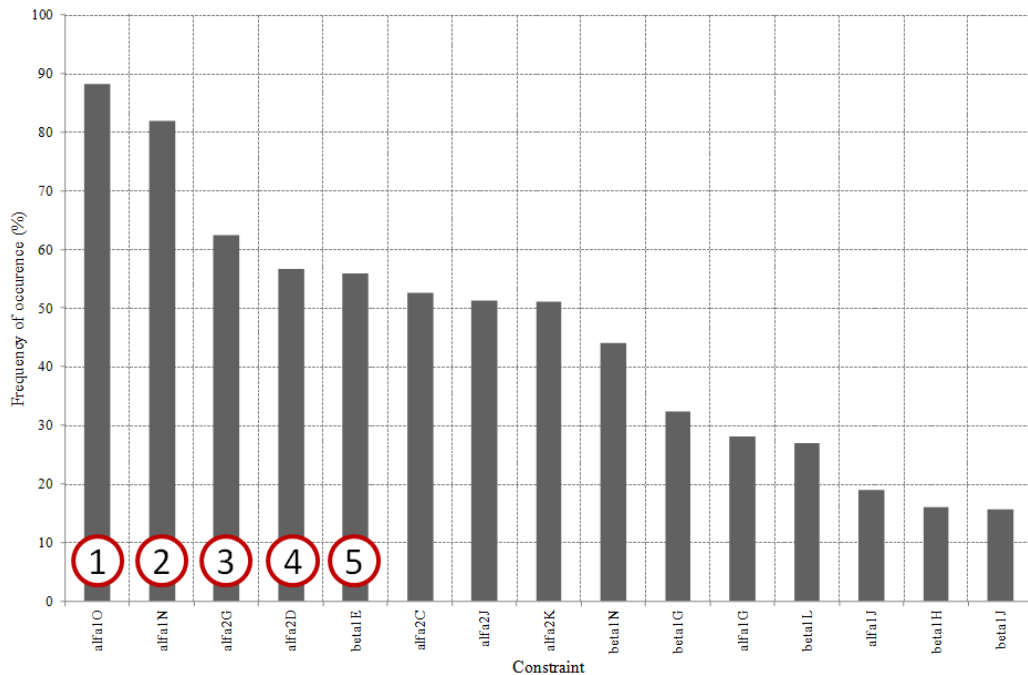


Figure 7.43. SCORE analysis of the line subject for optimisation of running cost, investment and lean buffer optimisation.

The results are very similar to the ones from the cost optimisation case and the data-mining studies. The main constraints are the cycle time in OP1O and the cycle time in OP1N limiting the throughput of the line. Hence, as long as the improvement costs are reasonable, the recommendations from the bottleneck study (constraints analysis) are very similar to the ones from the cost optimisation study. According to Dudas et al., (2012), the availability in OP1E is the most important decision variable for low running cost and low buffer capacity. This is also essential in the comparison between the SCORE analysis and the cost optimisation, since improvements of constraints 3 and 4 in the SCORE study were not allowed in the cost optimisation study. OP1E is revealed as constraint number 5 in the SCORE analysis.

7.4.5 Findings

Visual techniques for post-optimality analysis can be very useful for knowledge extraction as part of an innovization procedure supporting production systems improvement and development. The most important findings from this study are summarised below.

- The results from visual analysis can be comparable with the results from decision tree analysis.
- Random search methods can be used as a complement to MOO methods for the creation of rules with regard to parameter settings to avoid when designing high performing systems.
- Rules extracted from an initial study can be applied in a focused optimisation of a decision maker's preferred area of interest.
- A significant reduction of the necessary computational resources can be achieved by the application of rules from knowledge extraction. Optimisation with applied rules has the potential to find higher performance solutions, with less computational resources, compared to optimisation without rules.
- The results of the SCORE methods correspond very accurately with results from other optimisation studies and data mining methods while providing fast and simple analysis, especially when only minor costs are required to implement the proposed production system improvements.

7.5 A summary of the key findings

The framework proposed in Chapter 3 has been applied on a number of real-world industrial problems, in order to validate its usefulness for creating decision support. At the same time, the methods proposed in Chapters 4 and 6 have been enhanced, to some

extent. Various types of production systems and decision situations have been included, in the effort to strive for validation through multiple triangulation (Denzin, 2009). In all these cases, significant insights and decision support was obtained. Furthermore, the solutions implemented in real-world production have delivered performance fairly close to the predictions. Through these studies, it can be concluded that a solid proof of concept has been established regarding the usefulness of the framework in creating decision support for production systems design and improvement. The most important findings can be summarised as:

- MOO can be a powerful method for extracting knowledge of production system behaviour, serving as an important source for the creation of decision support within industry.
- The use of a combination of post-optimality analysis and advanced visualisation techniques, like 4D and PC plots, has shown to be very useful for the extraction of essential parameter settings from optimisation data and to gain knowledge about the problem to support decision-making.
- Including cost parameters and cost objectives in SMO enhances the capability of the method as a decision-support instrument within the industry. It has been adequately proven that such a financial-based SMO method can be very valuable for practical industrial applications.
- The SCORE analysis method has been applied on a real industrial problem and has revealed relevant improvement strategies with the advantage of indicating the type of constraint.
- There is a potential to combine the SCORE method with cost optimisation, in order to generate improvement strategies that take into account monetary aspects and not just constraints or bottlenecks. When applied within the framework for production systems decision support, the method can provide information on the most beneficial solutions from a cost perspective.

- Random search approaches can be used as a complement to MOO methods for the creation of rules regarding parameter settings to avoid, when designing high performing systems.
- Rules extracted from an initial study can be applied for the focused optimisation of a decision-maker's preferred area of interest.
- Significant reduction of the required computational resources can be achieved by the application of rules from knowledge extraction.
- Optimisation with applied rules has the potential to find solutions with higher performance, using less computational resources, compared to optimisation without rules.
- The results of the SCORE methods correspond very accurately to the results from other optimisation studies and data mining methods, while providing fast and simple analysis, especially when only minor costs are required to implement the proposed production system improvements.

7.6 Conclusions

The framework proposed in Chapter 3 has successfully been applied and verified on a number of real-world industrial problems. The integration of the models proposed in Chapters 4 and 6 has opened for opportunities to include more objectives in the creation of decision-making support and to accurately find essential constraints in production systems. In the effort to strive for validation by “multiple triangulation” (Denzin, 2009), several types of production lines and systems have been considered, in various decision situations with different decision makers. First, the procedures for simulation and optimisation have been tested. Then, an increasing degree of post-optimality analysis and cost modelling has successfully been applied. The special application of the framework for constraints/bottleneck detection, aka the SCORE-method, has been applied on a real-world scenario. Finally, the opportunities opened by knowledge extraction techniques have been explored in connection to the framework application

with cost modelling. The extraction of rules from data is an essential part of the framework, potentially creating valuable decision support, enhancing the quality and performance of optimisations, as well as shortening lead-times by reducing the computational resources required. The real-world independent application studies have all resulted in valuable decision information. It can be concluded that a solid proof of concept has been established for the application of the proposed framework on real-world industrial decision-making in a manufacturing management context.

Industrial application, results and verification

Chapter 8.

Discussions

This Chapter includes a broader discussion of the background to the research presented in Chapters 1 and 2, the framework proposed in Chapter 3, and the modelling techniques proposed in Chapter 4 to and including Chapter 6. In addition, the applications and verification presented in Chapter 7 are commented on, opportunities and limitations are considered, and some of the thoughts and insights gained during the work on this thesis are shared.

8.1 Industrial perspective

The difficult and competitive situation in the automotive industry is not just something identified through the literature review, it is also something experienced during the author's almost twenty years in engineering and managerial positions within industry. The development of vehicles and powertrains that address ever more stringent requirements on emissions and fuel consumption is occurring at a continuously faster pace year by year. This consequently requires that production systems are updated more frequently with shorter lead times, which further emphasises the urge for lower capital investment. Despite more frequently updated production systems, operations must also run smoothly and efficiently, in order to fulfil customer demand at low running costs, as well as stay competitive. In an attempt to undertake all these challenges, numerous manufacturing management paradigms and improvement methods, such as TPM, Six Sigma, ToC and adapted versions of TPS, (i.e. Lean), have been launched into the operations. TPM has been of great importance for equipment performance in combination with ToC, Six Sigma has contributed to improved processes, and Lean has been very useful in setting the standard at shop floor level, promoting the involvement

of workers and improving leadership, as prerequisites for organisational learning. While there are many benefits with all these paradigms and methods, there are also some additional drawbacks besides those highlighted and identified in Chapters 1 and 2. Often, considerable resources are required to implement and run these initiatives; however, improvements are not always consistent and tend to diminish after some time. Sometimes, when a new paradigm is introduced, previous ways of doing things are criticised and considered wrong, instead of focusing on their beneficial aspects. In other words, the best way of doing things should be sought instead of just following every new trend. In this context, the author agrees with Ignizio (2009) that a balanced approach, with regard to these paradigms, must be endeavoured. From this perspective, it is essential to preserve the advantages of existing procedures, when considering the application of the framework and the methods proposed in this thesis. The new framework and the methods presented in this work should be seen as one way of creating valuable information, in order to support high quality decision-making within manufacturing management.

8.2 Framework design

The main purpose of the proposed framework is to enable the transformation of data into knowledge that supports decision-making. One of the prerequisites, when designing the framework, was to make industrial implementation possible with reasonable efforts and that required inputs should preferably be aligned with data and information already available within industry. It is also believed that while the framework, to some extent, could be realised using currently commercially available software, it would be beneficial to develop dedicated software or a Decision Support System (DSS) that seamlessly supports all the steps in the application process. Applying each step of the process in various isolated software might be too complicated and time consuming to support decision-making in a flexible way. Moreover, there would be a risk for errors with the manual or semi-automated transfer of data between software tools. Even

though it is not in the scope of the thesis to develop such software, the framework design has been executed with software integration in mind. The order in which to perform the various tasks, presented in the generic process for the creation of decision support in Chapter 3 (Section 3.3), is just one perspective. It might be possible to do some of the tasks in another order, for example, it could be argued that defining the optimisation objectives should be done before creating or updating the simulation model. The reason for the currently proposed order is that the method requires a simulation model of the production system, regardless of the objectives to be evaluated, and it is beneficial to gain more understanding of the system and its behaviour through modelling, before the optimisation objectives are determined. The repetitive and interactive loops included in the process suggest that such decisions could be taken through an iterative process, rather than just sequentially through a limited number of sequential tasks.

8.3 New methods and algorithms

When this research started, there were some quite clear ideas about the creation of methods for cost modelling and sustainability modelling. With regard to existing modelling techniques, it was found that many of them were far too detailed to be applicable in the conceptual development of production systems. The struggle was to find an aggregation level that matched available production systems data and conceptual simulation modelling. Some ideas from project appraisal processes and TPM related work on transferring OEE improvement effects to the financial domain were considered. Establishing a relationship between the utilisation of production time and running cost was the key enabler for the design of the running cost model. An important decision was to align the information with annual values, in order to be able to use accounting information transparently. There are some limitations to a model with such an aggregation level, for example, the effect from increased sales due to improved production performance cannot be evaluated and the balancing of tasks between

operations might require more detailed models. Another limitation of the proposed model is that investments are not divided into amortised and non-amortised costs, compared to related work, such as that of Freiheit et al., (2007), which specifically considered amortised costs. However, the basic model design will allow the addition of other categories and, if more information is required for decision-making, other models and calculations could be added into the framework and applied within the proposed process for application or *a posteriori* with the results from the framework application as input.

The sustainability models were designed for integration with the cost models and one guiding principle was to align the sustainability modelling technique with the cost modelling technique, as far as possible. When discussing the sustainability models (besides the cost models) within industry, it is believed that while they surely could assist decision-making and including them is, without a doubt, “politically correct”, the main contribution to sustainability would be to operate the production systems for a shorter time, if possible, thanks to performance improvements obtained by the application of the other framework components. Presently, the opportunities and interest for a real-world application of the sustainability modelling techniques are limited, or more precisely, non-existent, when considering that priorities have to be made due to the limited production development resources.

The constraints/bottleneck detection technique, aka SCORE-method, proposed in Chapter 6, is the result of an attempt to solve a real-world problem. While trying to find the bottleneck in a production line during an urgent need to increase capacity and it was found that existing methods could not provide enough information, the basic idea for a new algorithm was born by combining SMO, ToC, and frequency analysis. After some prototyping, programming, and trial-and-error experiments, it was really exciting to realise that a new method of bottleneck detection had been invented. Through continued testing, applications, and verifications, it was evident that the original idea of combining SMO, ToC and frequency analysis for bottleneck detection works in practice. Some limitations were also identified and they are related to the dependency on an accurate

simulation model and the somewhat complicated, manual data processing, if the method is not automated. Another idea for an algorithm that gradually emerged during the development of the framework, in combination with cost models and discrete input parameters, was to conduct post-optimality analysis and search for rules in the data, by scanning the parameters, one by one, for step effects in the objective space. The advantage of such a method is that it can be executed and explained graphically, thereby, understanding it is believed to be straightforward from a decision maker's perspective. The potential to automate the graphical principle into a complete algorithm is outside the immediate scope of this thesis, but it can be seen that some technical problems need to be solved, for example, if the two-dimensional graphical method has to be extended into a multi-dimensional automated algorithm. Furthermore, the proposed framework and the connected models do not include the specific evaluation of quality related decision variables, because this is also outside the scope of the thesis. Nevertheless, to incorporate quality improvement decision variables as an additional component, in the secondary objective, seems to be a ready extension of SCORE. Such an extension would be most beneficial in order to investigate where to apply quality improvement resources and performing inspections.

8.4 Industrial Applications

The real-world application and verification of the framework has been enabled through highly valuable cooperation with industry. The main expectation, when these tests started, was to be able to produce enough results to establish a qualitative "proof of concept". However, some quantitative results were also established showing that fairly accurate estimations could be made with the proposed framework. Application and validation have been carried out in real projects, during the development and improvement of production systems. Insights into the importance of including enough parameters to truly optimise a system have been gained through the application studies. It has often been found that it is essential to consider several constraints, in order to gain

any significant improvement. To ensure confidentiality, some of the data used and the results presented had to be concealed and, in such cases, relations in the data were maintained. During the first real-world applications, several engineers connected to the specific studies revealed an interest and provided the required data and information, so that the initial simulation models could be created. As soon as the first results were presented, their interest increased and they wanted to take a greater part in the simulation modelling. With the improved and accurate models of the production systems, the prerequisites for the connection of cost models were in place. Assistance from accountants and controllers helped to prepare the required cost data. The support from management immediately increased, as monetary aspects were integrated into the framework and decision support could be created with these kinds of objectives in mind. The response from the author's colleagues in Manufacturing Engineering Management was to approve the complete implementation of a solution found by the application of the framework presented in Chapter 7 (Section 7.2). It was a great opportunity for the quantitative evaluation and verification of the framework, which cannot be easily done in other research studies. One year later, the selected solution was fully implemented and, after a two month testing period, the company could establish that the predictions made by the application of the framework were actually more accurate than they had expected. A fortunate circumstance was that the production volume during the test period was almost exactly the same as predicted in the forecasts. Production time could be reduced, in order to shut down operations and overtime on a more expensive shift. When the results were compared with the original running cost budget (forecast), together with accountants and controllers from the company, it was found that the estimated savings deviated just a few per cent from the predictions. At the same time, the initial results from the new SCORE method for finding constraints and bottlenecks were presented. The interest within the company continued to grow rapidly and several proposed studies had to be turned down, so that the most essential parts of the research could continue. After some discussions with the management, it was decided to allocate resources for technology transfer and the company has now started creating its own decision support process based on the proposed framework.

Another major Swedish automotive manufacturer is planning the same implementation of the framework. It is expected that the application of the framework will, in the near future, be more widely spread and more real-world, full-scale applications and validations can be done.

8.5 Some comments on results, validation and limitations

The framework has been developed and tested in close collaboration with the automotive industry. Despite the intention to produce generally applicable results, there could be a bias towards the type of operations within automotive manufacturing. However, by application on various lines, problems, and decision situations, it has become reasonably clear that as long as accurate simulation models of a system with relevant input and output parameters are available, the methodology is generally applicable.

When validating the cost model, it is not possible to establish the exact amount of the actual savings, since the reference is a forecast made in the conceptual phase. The forecast contains, e.g., assumptions based on the same costs for wages as the cost model. The estimated running cost, however, can be compared to the actual resulting running cost for validation.

One limitation might be if the models take a long time to run, since a number of generations of solutions must be created when working with genetic algorithms. Parallel computing and model aggregation can, to a great extent, compensate for those limitations and, in most cases, optimisation results can be produced within minutes or a few hours. The longest optimisation time experienced during the course of this research was one week, when 25 parallel processor cores were used in simulating 30 days of production for a very complicated system. Using approximately 150 input decision variables, the optimisation was run with 30 000 iterations (simulation run), each with 5 replications. The cost of the computing power required is not very high, when considering the potentially huge cost savings in real-world industrial decision situations.

It has also been shown in Chapter 7 (Section 7.4) that the required computational resources can be substantially reduced by interleaving optimisation and data mining, so that the rules extracted from an optimisation as a rough exploration of the decision space can be used to modify the original optimisation, to enable a more focused search of the decision maker's preferred region (see also Ng, et al., 2012).

In terms of evaluation speed, it can also be discussed that some of the production configurations shown in this thesis can be effectively modelled by analytical modelling methods, e.g., Li and Meerkov (2009), which could also dramatically reduce the computing costs and the optimisation running time. Nevertheless, in general, analytical methods require strict assumptions about the settings that can be modelled. For instance, only machine failure probability that follows Bernoulli or exponential distribution can be applied, when the system's theoretic modelling methods (Gershwin, 1997) are being used, which would greatly restrict the modelling capability when they are applied to real-world production lines. Actually, in a recent student project study conducted for a Swedish truck manufacturer, it was found that the machine failure rate follows a lognormal distribution, instead of the Erlang distribution that is commonly presented in simulation literature. At the same time, analytical modelling methods usually fall short of giving an accurate estimation of system performance, if complex flow and material handling is involved. There are also other studies showing the intricacies of analytical methods and they conclude that simulation modelling is more suitable for real-world system analysis (Wadhwa and Lien, 2012). Therefore, in order to provide a generic and flexible evaluative modelling for the optimisation, which can be applied to any type of production system flow, this thesis only considers DES as the sole evaluative modelling method in the framework.

Chapter 9.

Conclusions

In this chapter, the overall conclusions of the thesis are presented in Section 9.1 and the contributions to knowledge are summarised in Section 9.2.

9.1 Overall conclusions of the thesis

The major conclusions related to this thesis can be summarised as follows:

- A framework for the creation of decision support, using SMO, for the development and improvement of production systems, has been proposed, together with models for the simultaneous computation and evaluation of cost, sustainability, and production system related objectives. The integration of cost and sustainability models with production systems DES models and MOO enables the search for high-performing trade-off solutions with regard to several conflicting objectives from different disciplines. Techniques for knowledge extraction are applied to data within the framework and used to reveal hidden information and valuable design rules to the decision-maker. All together, the framework re-focuses the decision-making from being based mainly on raw data towards being an informed process based on the exploration, extraction, and elevation of knowledge.
- A new algorithm and a method for identifying and ranking constraints and bottlenecks in production systems are proposed as a special application of the decision-support framework. By optimising the most beneficial constraints to remove with minimisation the number of changes and simultaneous maximisation of throughput, input data for a frequency analysis is created. Based on ToC, the most frequently occurring constraints in the data are the most

significant ones to remove and, by plotting the results from the frequency analysis, the production system's bottlenecks (or constraints) can be presented in order of importance. Since the constraints are categorised into several types, the method takes bottleneck analysis a step forward by enabling the detection of not only where to improve, but also what kind of properties to improve, according to rank, in one single analysis run.

- The framework and the methods proposed have been tested through “laboratory” experiments and successfully applied on a number of real-world production system problems within the automotive industry. Through the application on various problems in different decision situations, it has been proven that the framework with its methods is capable of creating very valuable decision support for production systems development and improvement.

The framework resulting from this research addresses some major drawbacks with current methods of industrial analysis. The stochastic behaviour and variability of production systems are taken into account, by using simulation-based methods as a foundation for new methods. A complete system perspective is also supported by the simulation-based methods. The new framework is designed to reveal knowledge and trade-off information about high-performing solutions parameter settings and vital design principles to satisfy production systems improvement and design objectives. Production systems can be optimised with regard to several conflicting objectives simultaneously, including cost, sustainability, and technical system performance indicators (see Chapter 3).

The potential of applying SMO, taking into account financial objectives, such as investment and running costs, for decision-making support in designing and re-configuring production systems, has been explored. Evaluating several combined minor improvements with the help of MOO has enabled identifying a set of solutions that

reveal considerable financial improvement, which cannot be sought by applying any current industrial procedures. A running cost improvement of over 25% has been achieved and validated through industrial application with very limited investments. At the same time, throughput increased by more than 20%, see Chapters 4 and 7 (Section 7.2).

The entirely new method for constraints and bottleneck detection can be combined with the optimisation of other parameters, for prioritisation regarding certain objectives, such as investment. The optimal order of improvement can be ranked according to importance and it is possible to achieve a higher improvement rate with this new method, compared to existing methods used within industry, see Chapters 6 and 7 (Section 7.3). The use of a combination of post-optimality analysis and advanced visualisation techniques, such as 4D and PC plots, has shown to be very useful for the extraction of essential parameter settings from optimisation data and to gain knowledge about the problem, in order to support decision-making.

Knowledge extraction techniques can generate other advantages than just the creation of decision-support information. Rules extracted from the rough discovery of the objective space, based on experiments with random search methods such as LHS, can be applied in subsequent optimisations, thus substantially reducing the computational effort required by targeting optimisations towards areas of special interest to the decision-maker. Knowledge extracted from data generated by random search methods can be of value as complementary information to knowledge from optimised data. Since optimisation is effective in searching for high-performing solutions, there could be less or no information about solutions to avoid, in the resulting data. Hence, the use of complementary data from random search methods could enable the extraction of rules revealing parameter settings and designs that should be avoided, see Chapter 7 (Section 7.4). Rules extracted from a rough initial study of the objective space can be applied to focus optimisation towards a decision maker's preferred area of interest.

The computational resources required for production systems optimisation can be significantly reduced by applying the rules from knowledge extraction on the subsequent optimisation. The optimisation with the applied rules has the potential to find higher-performance solutions, using less computational resources, compared to an optimisation without rules.

The framework has been developed and tested in a number of experiments and applications which have proven that the proposed framework is very useful for the creation of manufacturing management decision support and that such a methodology can contribute substantially to profitability, when applied within the automotive industry. It can be concluded that a solid proof-of-concept has been established for the application of the proposed framework on real-world industrial decision-making, in a manufacturing management context (see Chapter 7).

9.1.1 Contributions to knowledge

Specific contributions to knowledge resulting from this research are summarised below:

- The exploitation of a new framework for the creation of decision support, using simulation-based MOO with post-optimality analysis, has been proven to substantially improve the prerequisites for informed decision-making within the development and improvement of production systems.
- The development of aggregated cost and sustainability models for integration with DES models has enabled the introduction of cost and sustainability optimisation functionality into the framework, significantly expanding the opportunities for creating production systems decision support, with regard to objectives from several essential domains, to be used within manufacturing management.

- The development and application of knowledge extraction techniques have opened some new opportunities for decision-making, by revealing and transforming hidden knowledge in data into essentially understandable information that can be presented in a clear context to decision makers.
- A new bottleneck detection technique developed by the author leads to a new way of approaching production systems improvement. Bottlenecks and constraints can be identified, together with properties required for improvement, and ranked in order of importance, in one analysis run. The method can provide information on the most beneficial solutions from a cost perspective. Furthermore, the method can reveal better improvement strategies for production systems, compared to some other well-established techniques, such as shifting bottleneck detection. In summary, a method providing a new level of information for the support of manufacturing management decisions has been developed.
- Experiments and real-world application have adequately proven that a financial-based SMO method can be very valuable for practical industrial applications.

Conclusions

Chapter 10.

Future work and outlook

In this Chapter, some thoughts on future work are shared, together with expectations for the future.

There is an opportunity to expand the cost modelling technique to cover other business perspectives and objectives, e.g., when increased throughput from a constrained line would result in increased sales. Investment models should be updated to include the amortised and non-amortised categories. Sustainability modelling and optimisation would benefit from more testing with various parameters and objectives. Yield optimisation could be included in waste modelling and more data could improve energy consumption aggregation strategies.

Such a specific task as the SCORE constraints and bottleneck detection method has a potential for improved performance, by the development of dedicated MOO-algorithms or more specialised settings, when using existing algorithms. Other constraints could also be included in the method, as well as opportunities to expand the use into other types of applications. So far, the implementation of the method has been carried out in the form of prototypes and demonstrator models dedicated to specific simulation models. The complete automation of all steps in the SCORE method is required before a wider use and actual industrial implementation can be achieved. The framework would benefit from techniques with the ability to automatically stop the optimisation at some degree of convergence to a Pareto frontier and including such techniques in the optimisation tools would also be very useful.

The potential for the integration of quality-related analysis tasks with the SCORE-method, connected to the cost and sustainability models, should be evaluated, in order

to determine whether the method could reveal where the application of quality improvement resources would be most beneficial or where to perform inspections.

The proposed visual method of finding clusters in discrete parameters from optimisation could also be automated, by searching through each such parameter for steps in the objective values. The objective space might have to be divided into regions based on another objective, in order to search for clusters in the complete data.

Finally, an interesting emerging research is the development of new algorithms for multi-objective optimisations and the automation of innovization methods. To merge computer-aided innovation methods and optimisation with boundary expansion could open new opportunities for conceptual systems development. With regard to application areas, various approaches for multi-level production system optimisation and the complete optimisation of new products, production systems and supply chains simultaneously, are worth mentioning as being very challenging and interesting tasks for the future. Hopefully, the framework and methodology introduced in this thesis will naturally lead to the research of a new generation of IDSS, which would provide more advanced intelligent functions to assist the decision makers.

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Bibliography

Appendix

Appendix 1. Cycle times for all stations with min, mode and max related to the triangular distribution related to the experiments in Chapter 7 (Section 7.1).

STN	min	mode	max				
S010	60,3	67	73,7	S240	59,31	65,9	72,49
S020	65,88	73,2	80,52	S250	36,18	40,2	44,22
S030	55,98	62,2	68,42	S260	31,95	35,5	39,05
S040	55,26	61,4	67,54	S270	52,02	57,8	63,58
S050	62,46	69,4	76,34	S280	32,31	35,9	39,49
S060	0	0	0	S290	0	0	0
S070	0	0	0	S300	37,89	42,1	46,31
S080	0	0	0	S310	16,74	18,6	20,46
S090	0	0	0	S320	59,13	65,7	72,27
S100	71,37	79,3	87,23	S330	71,19	79,1	87,01
S110	56,79	63,1	69,41	S340	63,09	70,1	77,11
S120	60,21	66,9	73,59	S350	53,55	59,5	65,45
S130	61,02	67,8	74,58	S360	43,2	48	52,8
S140	48,15	53,5	58,85	S370	32,58	36,2	39,82
S150	67,05	74,5	81,95	S380	36,9	41	45,1
S160	62,37	69,3	76,23	S390	41,4	46	50,6
S170	67,59	75,1	82,61	S400	60,66	67,4	74,14
S180	45,81	50,9	55,99	S410	47,61	52,9	58,19
S190	48,69	54,1	59,51	S420	40,68	45,2	49,72
S200	66,15	73,5	80,85	S430	29,79	33,1	36,41
S210	37,35	41,5	45,65	S440	47,34	52,6	57,86
S220	43,74	48,6	53,46	Sum (s)	1950,75	2167,5	2384,25
S230	21,06	23,4	25,74	(minutes)	32,5125	36,125	39,7375

(Stations with times in seconds)

Appendix 2. Recipe for aligned manning based on the SMO study presented in Chapter 7 (Section 7.1).

No of operators	Loop 1	Loop 2	Through-put
2	1	1	2,48
3	2	1	3,06
4	2	2	4,96
5	3	2	6,11
6	3	3	7,43
7	4	3	9,17
8	4	4	9,90
9	5	4	12,22
10	5	5	12,37
11	6	5	14,83
12	7	5	15,26
13	7	6	17,30
14	8	6	18,31
15	8	7	19,75
16	9	7	21,32
17	9	8	22,19
18	10	8	24,33
19	10	9	24,64
20	11	9	27,05
21	12	9	27,35
22	12	10	29,46
23	13	10	30,30
24	13	11	31,85
25	14	11	33,27
26	14	12	34,22
27	15	12	36,11
28	15	13	36,52
29	16	13	38,67
30	17	13	38,91
31	17	14	40,80
32	18	14	41,54
33	18	15	42,69
34	19	15	43,63
35	19	16	43,95
36	20	16	44,40

(Throughput in JPH)

Appendix 3. Process change scenario description with investments. Related to Chapter 7 (Section 7.2).

Sub-categories, shown in Appendix 1, are used for investment estimation and in order to prepare correct accounting of all related costs (real-world example).

Category	Sub-category
Process related prerequisites	
Impact per operation, station or facility	<ul style="list-style-type: none"> Changed function or Reconstruction New operation Replacement Renovation/repair Shutdown (Capacity related) Scrapping
Manhours and staffing	<ul style="list-style-type: none"> Manhours in TMU Staffing impact (required number of people)
Monetary categories	
Investments	<ul style="list-style-type: none"> Facilities, land and buildings Equipment Special tooling Software Spare parts
Facility related expenses	<ul style="list-style-type: none"> Facilities, land and buildings Equipment Special tooling Software Parts and material for equipment and system verification
Project management cost	<ul style="list-style-type: none"> Project Management and Manufacturing Engineering Maintenance specialists Information Technology Material Planning and logistics Buildings Planning others
Implementation cost	<ul style="list-style-type: none"> Production participation Training Industrial running in

Running costs	Expenses
	Wages
	Freights and packaging
	Supplies
	Tools
	Maintenance
	Tools Maintenance
	Depreciations
	Process Media
	Scrap
	Environmental (e.g. cost for waste and landfill)
	Others

Appendix 4. Cost model validation details. Related to Chapter 7 (Section 7.2.).

Industrial cost model application study, Running cost, original project forecast before optimisation vs. validation

Category	Original Forecast (M\$)	Validation Actual* (M\$)	Difference (M\$)
Scrap	0.199	0.098	0.100
Wages	2.766	1.647	1.119
Supplies	0.306	0.201	0.105
Tools	0.421	0.488	-0.067
Machine maintenance	0.922	0.458	0.464
Tools maintenance	0.332	0.200	0.132
Bought hours and services	0.030	0.407	-0.377
Others	0.026	0.016	0.010
Crediting	-0.065	-0.026	-0.040
Total sum	4.936	3.489	1.447

(Original-Actual)

Estimated from optimisation (M\$)	3.610	
Actual* (M\$)	3.489	
Deviation (M\$)	-0.121	(Actual-Estimated)
Deviation (%)	-3.47%	((Actual-Estimated)/Actual)

* The two months of validation (january and february) was estimated to contribute with 18% of the annual volume and cost based on other budget examples. See Chapter 7, Table 7.5 for such an example.

The original forecast is from the conceptual phase.

The actual figures are from two validation months.

To ensure confidentiality, some of the data used and the results presented had to be concealed and, in such cases, relations in the data were maintained.

Appendix 5. Software, genetic algorithm and settings

Simulation, optimisation and visualisation platform:

FACTS Analyzer 1.0 (Ng et al. 2007) with its Optimize Client and Optimize Browser connected to Tecnomatix Plant Simulation, version 9.04:

Facts Analyzer Professional is commercially available through Evoma AB:

Evoma AB
Box 133
SE-541 23 Skövde
Sweden

<http://www.evoma.se>

Tecnomatix Plant Simulation is commercially available through Siemens AG:

Siemens AG
Wittelsbacherplatz 2
80333 Munich
Germany

http://www.plm.automation.siemens.com/en_us/products/tecnomatix/plant_design/plant_simulation.shtml

Genetic Algorithm and general settings

When referring to general purpose genetic algorithms the one used throughout the work in this thesis has been NSGA-II (Deb, 2001) and its implementation in Facts Analyser.

The NSGA-II original implementation source code is available through Kanpur Genetic Algorithms Laboratory, Kanpur, India:

<http://www.iitk.ac.in/kangal/codes.shtml>

The following general settings have been applied.

Crossover operator: Uniform Crossover

Crossover probability: 0.9

Blend crossover operator variation parameter, BLX- α : 0.5

Simulated Binary Crossover parameter variation parameter, SBX η_c : 0.5

Mutation operator: Uniform Range

Mutation Probability: $1/(\text{Number of input parameters})$

Polynomial Mutation, η_c : 5

Population size: 50 if the number of input parameters < 50 , 100 if the number of input parameters > 50 .

Significant domination confidence: N/A

List of publications and awards

Peer-reviewed Journals

Pehrsson, L., Ng, A.H.C. and Stockton, D.J. (2013) Industrial Cost Modelling for Multi-Objective Optimisation of Production Systems, *Computers and Industrial Engineering*. (In press) Available online 24 August 2013.

The complete content is the contribution by the author of this thesis under supervision by Ng and Stockton.

This paper is related to the Chapters 2, 3, 4 and 7, section 7.2.

Dudas, C., Ng, A.H.C., **Pehrsson, L.** and Boström, H. (2013). Integration of data mining and multi-objective optimization for decision support in production system development, *International Journal of Computer Integrated Manufacturing*. DOI:10.1080/0951192X.2013.834481

The framework, case study, and modeling are the contributions by the author of this thesis. The data mining method is the contribution by Dudas. Supervisors: Ng and Boström.

This paper is related to the Chapters 2, 3, 4 and 7, sections 7.2 and 7.4.

Pehrsson, L., Ng, A.H.C. and Bernedixen, J. Automatic bottleneck detection and manufacturing management using multi-objective optimization and post-optimality analysis, submitted to *Omega: The International Journal of Management Science*.

The framework, the complete procedure, the experiments, and the analysis are the contributions of the author of this thesis. Some of the model

development, not included in this thesis, is the contribution of Bernedixen. Supervisor: Ng.

This paper is related to the Chapters 2, 3, 4, 6, and 7, section 7.3.

Book Chapter

Pehrsson, L., Ng, A.H.C. and Bernedixen, J. (2011). Multi-objective production system optimisation with investment and running costs. In *Evolutionary Multi-objective Optimization in Product Design and Manufacturing*, L. Wang, A. Ng, K. Deb (eds.), Springer. 431-454.

The framework, the complete procedure, the case study, and the analysis are the contributions by the author of this thesis. Programming, not included in this thesis, is the contribution of Bernedixen. Supervisor: Ng.

This paper is related to the Chapters 2, 3, 4 and 7, section 7.2.

International Conferences

Pehrsson, L., Ng, A.H.C., Bernedixen J. and Stockton, D.J. (2013). Sectioned walking-worker lines with loop balancing. In the *Proceedings of the Industrial Simulation Conference, ISC'2013*, May 22-24, 2013, Ghent, Belgium. 187-191.

The complete content is the contribution by the author of this thesis under supervision by Ng and Stockton.

This paper is related to Chapters 2, 3, and 7, section 7.1.

Pehrsson L. and Ng A.H.C. (2013). Decision-making in conceptual AGV systems design using simulation-based optimisation. In the *Proceedings of the Industrial Simulation Conference, ISC'2013*, May 22-24, 2013, Ghent, Belgium. 171-176.

The complete content is the contribution by the author of this thesis under supervision by Ng.

This paper is related to the Chapters 2, 3, and 7, Section 7.1.

Ng. A.H.C., Dudas, C., **Pehrsson, L.** and Deb, K. (2012). Knowledge Discovery in Production Simulation by Interleaving Multi-Objective Optimization and Data Mining. In *Proceedings of the 5'th Swedish Production Symposium (SPS'12)*, Linköping, Sweden, 6-8 November 2012. 461-471.

The framework and the case study are the contributions by the author of this thesis. The data mining method is the contribution by Dudas. The interleaving procedures are the contribution by Ng. The algorithms and innovization principles are the contribution by Deb.

This paper is related to the Chapters 2, 3, 4 and 7, sections 7.2 and 7.4.

Siegmund, F., Ng, A.H.C., Bernedixen, J., **Pehrsson, L.** and Deb, K., (2012). Reference Point-based Evolutionary Multi-objective Optimization for Industrial Systems Simulation, Winter Simulation Conference 2012, Berlin, Germany.

The bottleneck detection method is the contribution by the author of this thesis. The algorithm, not included in this thesis, is the contribution by Siegmund. Programming, not included in this thesis, is the contribution of Bernedixen. Supervisors: Ng and Deb.

This paper is related to Chapter 6.

Pehrsson L. and Ng A.H.C. (2011). An applied framework for simulation-based multi-objective production system optimisation within production system development, in the *Proceedings of the Industrial Simulation Conference, ISC'2011*, June 6-8, 2011, Venice, Italy. 121-128.

The complete content is the contribution by the author of this thesis under supervision by Ng.

This paper is related to Chapters 2, 3, 4, 5, and 7, section 7.1.

Pehrsson L., Ng A.H.C. and Bernedixen J. (2011). Multi-objective production system optimisation including investment and running costs, in *Proceedings of the 4th Swedish Production Symposium, SPS11*, May 3-5, Lund, Sweden. 55-62.

The framework, the complete procedure, the case study, and the analysis are the contributions of the author of this thesis. Programming, not included in this thesis, is the contribution of Bernedixen. Supervisor: Ng.

This paper is related to Chapters 3, 4 and 7, sections 7.2.

Ng, A.H.C., Jägstam, M., **Pehrsson, L.** and Deb, K. (2011). Improving Factory Productivity and Energy Efficiency through Holistic Simulation Optimisation. *The 21st International Conference on Multiple Criteria Decision Making*, 13-17 June, Jyväskylä, Finland. (Abstract and presentation).

The framework and the case study are the contributions by the author of this thesis. Simulation modelling procedures are the contributions by Jägstam. Interleaving procedures are the contribution by Ng. The algorithms and innovization principles are the contribution by Deb.

This paper is related to Chapters 3, 4 and 7, sections 7.2 and 7.4.

Awards

Best Paper Award in Industrial Automation at SPS'12 for the paper:

Ng, A.H.C., Dudas, C., **Pehrsson, L.** and Deb, K. (2012). Knowledge Discovery in Production Simulation by Interleaving Multi-Objective Optimization and Data Mining. In *Proceedings of the 5'th Swedish Production Symposium (SPS'12)*, Linköping, Sweden, 6-8 November 2012. 461-471.

Volvo Cars Technology Award 2013 for the industrial project connected to this thesis work.