Application of Performance Measurement on Manufacturing Simulations for Knowledge-Based Decision Support

by

Johan Lorentzon and Johan Fredlund

Submitted to the Department of Engineering Logistics
in partial fulfillment of the requirements for the degree of

Master of Science in Industrial Engineering, Engineering and Management

at the

FACULTY OF ENGINEERING (LTH),

LUND UNIVERSITY

June 2017

Application of Performance Measurement on Manufacturing Simulations for Knowledge-Based Decision Support

by

Johan Lorentzon and Johan Fredlund

Submitted to the Department of Engineering Logistics
on June 7, 2017, in partial fulfillment of the
requirements for the degree of
Master of Science in Industrial Engineering, Engineering and Management

Abstract

Manufacturing systems are becoming increasingly more complex at the same time as competition requires manufacturers to continuously improve their effectiveness and efficiency. The use of discrete event simulation to model manufacturing systems is well-established and generally considered to be the method of choice when analysing what-if scenarios. Simulation is currently predominantly applied when evaluating manufacturing system design and manufacturing rules and policies. These applications studies specific attributes and dimensions of the manufacturing system. To make full use of simulation-based decision-support in operations and inventory management, a performance measurement system needs to established to enable evaluation of simulated scenarios.

In this study, manufacturing simulation and knowledge-based decision support are linked to performance measurement practises used on real systems. By examining the characteristics of manufacturing simulation applications as well as the modelling conditions of discrete event simulation, measurable performance dimensions on manufacturing simulations are identified. Furthermore, a proposition on how to design a manufacturing simulation and a performance measurement system to provide effective decision support is formulated. Based on this, the authors present a suggestion for a manufacturing organisation on how they should develop their simulation-based decision support system.

Thesis Supervisor: Jan Olhager
Title: Professor

Preface

Writing this thesis has indeed been a challenging task; from defining a purpose and ploughing through hundreds of reserach articles and books, to transcribing more than 15 hours of recorded interview material and wrapping it all up in a few meaningful conclusions. Through motivation, Grönt & Gott and too few hours of sunlight, we not only managed to finish in time, but also ended up with a thesis we are proud to put our name on.

We would first like to thank the unnamed organisation, i.e. Company X, which invited to spend our last semester at university delving into manufacturing literature. We would further like to express our great gratitude to everyone who participated in this in study, without whom this thesis would not have been possible. We would also like to give a special thanks our supervisor, Professor Jan Olhager. Finally, and furthermost, we thank our families, friends and fellow classmates who made the years of studying both durable and fondly memorable.

Johan Lorentzon & Johan Fredlund
Lund, June 7, 2017

Contents

List of Figures

List of Tables

List of Abbreviations and Acronyms

CF . . . . Cash flow
DES . . . . Discrete event simulation
DSS . . . . Decision support system
DSSS . . . . . . Decision simulation support system
EOQ . . . . . . Economic order quantity
ERP . . . . . . Enterprise resource planning
FGW . . . . . . Finished goods warehouse
JIT . . . . Just-in-time
KPI . . . . Key Performance Indicator
MCP . . . . . . Manufacturing competitive priorities
MFG . . . . . . Manufacturing
MPS . . . . . . Master production schedule
MPA . . . . . . Master plan adherence
OEE . . . . . . Overall equipment effectiveness
PM . . . . Performance measure
PMS . . . . . . Performance measurement system
ROI . . . . Return on investment
SCI . . . . Simulation-based Constraint Identification
SCM . . . . . . Supply chain management
SCPM . . . . . Supply chain performance measurement
SOT . . . . . . Shipping on-time

SPC . . . . Statistical process control

TDABC . . . . Time-driven activity-based costing

TOC . . . . . . Theory of Constraints

WIP . . . . . . Work-in-process

Chapter 1

Introduction

This chapter will outline the foundation of the study. First, it will cover a background of the research topic and contextualise the study. Thereafter, a description of the problem will be provided, followed by the formulation of the research purpose, research question and objective of the study. Last, this chapter will state the delimitation of the study as well as motivate its contribution.

1.1 Background

This section will introduce the research topic and present the premise of the study. In the first part, the theoretical background will be discussed, including simulation and manufacturing, decision-making and decision support, as well as evaluation of manufacturing simulations. The second part will cover a practical background, briefly introducing the unit of analysis for the case study.

1.1.1 Simulation in Manufacturing

As manufacturing companies today strive towards improving efficiency and effectiveness in their operations, they also find themselves in a rapidly changing environment, imposing various requirements and constraints. This makes change and operational improvement a daily concern for many manufacturing facilities. In order to know what to change, how to do it, and the impacts of different scenarios, there is a need to model the manufacturing system. However, in many cases, manufacturing and logistics processes have grown into complex networks, sometimes with hundreds of different articles, which further consist of multiple components and sub-components. Being able to build a mathematical model representing such a network, which makes reasonably accurate predictions of real outcomes, is indeed a difficult matter (McGarvey & Hannon, 2004).

The difficulty of modelling a manufacturing system analytically is not only caused by the complexity of the many production flows in the system, but also largely due to its inherent variability. Besides the more direct variability caused by customer demand and supplier deliverability, the root of the variability is the process time variability at each workstation on the shop floor. It is mainly caused by natural minor fluctuations such as differences in operators, machines and material, as well as random outages, setups, operator availability and rework (Hopp & Spearman, 2008). In turn, the process time variability causes variability in the workflow, as the variability at one workstation might have effects on other workstations (Hopp & Spearman, 2008). The variability can be explained as stochastic processes, and in theory, for instance the expected throughput can be computed analytically. However, the complexity of the system as well as the many interdependent stochastic processes makes the computation impossible in practice.

An alternative, or rather a complement, to analytic modelling of manufacturing systems is to use discrete event simulation (DES), which has been used extensively in manufacturing since the 1960s (AlDurgham & Barghash, 2008). The main drivers of using simulation is to reduce running costs, increase productivity, and increase deliverability in order to increase profitability and competitiveness (Sundkvist et al., 2012). According to AlDurgham & Barghash (2008), the most common applications for using simulation in manufacturing are:

1) material handling;
2) layout;
3) sequencing and scheduling; and
4) decision support for the manufacturing strategy.

Simulation provides a solution to model the dynamics of a manufacturing system. Although simplifications and assumptions of the manufacturing system need to be made, the simulations are able to capture the variability and the complex flow network of the manufacturing system in a way that is impossible analytically. Furthermore, a DES model can be used to study and measure the behaviour of a variety of different parameters and sub-processes in the system, and thus reveal potential bottlenecks, poor utilisation and other forms of inefficiencies that are not obvious. As a result, DES is a useful tool for locating improvement areas in the production system (McGarvey & Hannon, 2004).

A simulation model is also highly flexible, as it is generally easy to change variables and modify the shop-floor layout to test different scenarios. Another advantage of using simulation is that it is possible to study the effects of manufacturing scenarios on multiple processes outside of the actual manufacturing flow, e.g. the finished goods warehouse (FGW).

1.1.2 Decision-making and the need for support

The need for modelling complex manufacturing systems is closely related to a need for support in decisions in general. Predicting the effects of decisions in complex systems can be difficult, even for experienced decision-makers, especially when the external environment is changing. As Axelrod & Cohen (1999) illustratively state in relation to decision-support:

> *"The hard reality is that the world in which we must act is beyond our understanding"* (Axelrod & Cohen, 1999, p. xvii)

In addition to the fact that the actual task of making decisions is becoming increasingly difficult, one can also argue that the quality of decisions in this context also needs to increase:

> *"As the decision-making world becomes more complex, it becomes increasingly difficult to anticipate the result of our decisions, and our decision-making processes must become as effective as possible."* (Bennet & Bennet, 2008, p.5)

1.1.3 Evaluating scenarios in manufacturing simulations

Whether the purpose of the simulation is to test scenarios to find an optimal set of parameters, or to test the impacts of a certain set of parameters, the performance of simulation must be evaluated in order to make a decision. To evaluate the performance of simulated scenarios, the vast amount of operational data that can be produced by a simulation model needs to be processed. When evaluating organisational performance in general or manufacturing systems specifically, it is done using specified sets of performance measures that represent the relevant dimensions and drivers of performance.

Stretching back to early 20th century and exploding in the 1990s, performance measurement is now a well researched field. Numerous work have been done on both designing and evaluating performance measurement systems in multiple settings and scopes (Gunasekaran & Kobu, 2007). It is important to note that while the field is well researched on real manufacturing systems, the virtual setting of simulated manufacturing systems is subject to other constraints and possibilities. Previous research, such as Sundkvist (2014) and Pehrsson (2013), has studied specific simulation-based performance measurement in manufacturing, e.g. productivity and cost. However, the authors have not found any research taking on a comprehensive view of the conditions of simulation-based manufacturing performance measurement.

1.1.4 Internal view

Company X

The study took an in-depth look at one specific manufacturing company, which hereinafter is referred to as "Company X". Company X is a large manufacturer of wooden and wood-based products, with multiple factories across Europe. Part of a corporate group, Company X is an internal supplier to the group's retail branch and competes with external suppliers. One of their goals is to be a competitive actor in the industry, in order for the group to obtain a better negotiation position against their external suppliers.

Company X has on some occasions adopted discrete-event simulation to model their manufacturing systems as decision-support in projects regarding changes to layout and equipment as well as factory design. However, they have experienced problems with using simulation, mainly due to issues with interpreting and evaluating the simulation output. This led to low implementation rate of simulated projects as well as a scepticism towards the usability of simulation as decision support.

Notably, the simulations have not been conducted by the organisation itself but outsourced to a consultancy firm. Hence, Company X's experience with simulation is limited to defining requirement specifications as well as analysing and interpreting the results as provided by the consultancy firm.

Factory 1

One of the factories of Company X was "Factory 1", which produces a wide selection of Company X's product range in a make-to-stock continuous-flow production. Due to their geographical location, Factory 1 is challenged by noncompetitive costs of salary and high distribution costs in comparison with other factories at Company X. As a result, Factory 1 has in general adopted a progressive position in implementing new ideas and improvements to achieve competitive advantage. Factory 1 is further one of the factories at Company X which previously has adapted simulation in project form.

1.2 Problem description

Company X is initiating a pilot test of implementing continuous use of simulation at Factory 1. Alongside with being able to simulate changes to layout, equipment and product mix, they are also planning to incorporate simulation-optimisation on production planning and scheduling. If the pilot is successful, the goal is to implement the simulation at other Company X factories. Based on their previous experience, Factory 1 has stressed the necessity of being able to better evaluate the performance of simulated scenarios to enable adequate decision-support. Company X has proposed that cost is an attractive measure for evaluation due to its simplicity and comparability, although there is no certainty as to whether this indeed is the best option, or even possible. They have also expressed an interest in the relation between financial and non-financial performance measures. This includes the questions if and how, it would be possible to relate or translate operational performance improvements into quantified financial impacts. In addition, what implications simulation would have on the selection of performance measures is another area of interest.

As the research client, Company X have pointed out two main objectives:

Obj1 To find what types of performance measures can provide with credible and understandable decision support on simulations, especially concerning financial performance measures.

Obj2 To map out appropriate sets of performance measures for different application areas of simulation-based decision-support.

1.3 Purpose, research questions and objectives

The purpose of this study is to investigate which performance measures enables comparable and credible evaluation of simulated manufacturing scenarios to support decision-making.

Based on the purpose, three research questions were formulated:

RQ1 What specific conditions does simulation-based decision-support put on the selection of performance measures and the design of a PMS, as opposed to performance measurement in a real system?

RQ2 What performance measures should be selected in a PMS in simulation-based decision-support, depending on the areas of application?

RQ1 is focused on developing grounded theory on how the performance of a manufacturing system can be measured in a simulation, as well as the possibilities, limitations and conditions that simulation itself has in performance measurement. Answering RQ1 is also a prerequisite to understanding what measures to use, and thus to answer RQ2. Following, RQ2 is closely related to the practical purpose of the study and aims to connect the academic view with the corporate view of preferable performance measures. Answering RQ2 allows for selecting the specific measures to use in the context of simulation-based decision-support in manufacturing, in different application areas. Finally, RQ2 further deals with how the most relevant performance measures found can be combined, essentially forming a Performance Measurement System.

1.4 Delimitations

The study will investigate performance measures of a manufacturing system which is delimited to the shop floor and finished goods warehouse. Thus, no other parts of the supply chain such as suppliers, material warehouses and distribution will be considered. Furthermore, the study will neither cover why production improvements are beneficial, nor how to improve performance for a production process, the company or in general. It will rather focus on how to measure the performance of improvements to support decision-making.

How to develop and conduct manufacturing simulations in general will also be excluded, although, modelling requirements regarding what the necessary operational outputs are for computing relevant performance measures will be discussed. The study will also exclude performance reverse-engineering. In other words, it will not cover what actions should be implemented to reach a specific performance objective, but rather focus on measuring the performance impact of a decision. Furthermore, the study is not focused on capital budgeting or financial evaluations of investment decisions in general.

1.5 Contribution

There is a substantial amount of research covering simulation, decision-making, decision-support and performance measurement in manufacturing. Among these are several papers with important contribution to this study. Leong et al. (1990) and Chryssolouris (2006) provide a solid understanding of the nature decision-making and the relation to manufacturing strategy. AlDurgham & Barghash (2008) discuss applications for simulation in manufacturing relations between different decision areas. Gunasekaran et al. (2004), Neely et al. (1995) and Beamon (1999) form the basis on the selection of performance measures and design of performance measurement systems. Pehrsson (2013) provides the most comprehensive study on the subject, as the author proposes a comprehensive framework and establishes a proof-of-concept for using simulations-based multi-objective optimisation for decision-support in manufacturing. While he covers costing, he does not focus on the selection of performance measures in general.

The authors have found no study that focuses on the selection performance measure and design of a performance measurement system for decision-making on simulated manufacturing. The contribution of the study will be an understanding of how performance measures can improve the use of simulations as decision-support and increase the credibility of simulation results. The contribution to manufacturing businesses will be a better understanding of the link between operational and financial metrics for stakeholders on various organisational levels and with different backgrounds.

Chapter 2

Methods

The objectives of this chapter are to describe and motivate the choice of research methodology for conducting this study and answering the research questions. This includes the choice of research philosophy, research approach, research strategy and research design. Moreover, the chapter will specify which methods were chosen and how they were used as well as how the collected data was analysed. Finally, the chapter will discuss quality of the study in terms of credibility, validity, transferability and reliability.

2.1 Research paradigm

This section will start by outlining the adopted philosophical view, reviewing the authors' stance on the three aspects of research philosophy which influenced the way the research process was approached, i.e.: *epistemology*, *ontology*, and *axiology* (Saunder et al., 2007). Thereafter, the research approach will be discussed and the choice of an inductive approach motivated. The research philosophy and the research approach supported the choice of research strategy by indicating if the approach to answer the research questions should be explorative. The philosophy, approach and strategy also clarified the choice of research design, i.e. what kind of data to collect and from where, as well as how the data should be interpreted. Last, the research traditions associated with the different approaches aided in adapting the research design to constraints, such as limited data and lack of theory or knowledge.

2.1.1 Research philosophy

The research philosophy is related to the development of knowledge and its nature. The importance of declaring the research philosophy is that it has dictated how the research questions were to be answered and what assumptions the authors made about the way they see the world.

The authors adopted a pragmatic epistemic view in this study, letting the research questions be the main determinant of research philosophy. Instead of adopting a defined stance on e.g. *positivism*, *realism*, or *interpretivism*, the authors claimed it was reasonable that multiple views could be adopted to obtain knowledge depending on their fit to each research question. The authors used an evolutionary view on the use of methods and approaches, with the aim of choosing the methods according to what is appropriate given the situation. As such, the view was that part of a study might be characterised by interpretivism, while another by positivism, without there being a contradictions between the legitimacy of the knowledge. The authors viewed that dismissing either knowledge from theory, measures or subjective interactions as invalid would inhibit the quality of the results.

The authors' position regarding ontology was that the distinction between objectivism and subjectivism were deemed unnecessary and practically unrealistic. The foundation of this stance was the acknowledgement of the existence of both an objective and subjective reality depending on the context, and that subjective realities in many cases can be collectively generalised as an objective reality. Again, this position is cohesive with the pragmatic view. Regarding axiology, the authors' background in natural sciences and engineering affected the preference of approaching research in an objective manner and that the research should be value-free to uphold validity. However, the authors maintained that a truly value-free and unbiased approach is in practice not achievable when the research is not driven by objective truths, e.g. as in mathematics or physics. As soon as subjective interpretation is involved in the research process, the authors asserted that the research will not be value-free.

2.1.2 Research approach

While the focus of this study was an under-researched subject, the theory related to the subject, i.e. decision-support, performance measurement, and DES in manufacturing, were well-researched. The literature thus provided sufficient amount of substance to develop a thorough theoretical frame of reference for the research topic, which might have suggested a deductive approach. Although, formulating a hypothesis by its formal definition is only valuable when it can be adequately tested. To the extent of the authors' knowledge, continuous use of simulated manufacturing requiring a system for evaluating performance was at the time severely limited. Trying to formulate a conclusive verification or rejection of the hypothesis would therefore not produce a reliable result, which indicated that a deductive approach was not fitting. The rigid methodology of deduction and the finality of the choice of theory and hypothesis was further seen as constraining alternative explanations of phenomena.

Rather than testing and verifying a theory, the inductive approach focuses on developing theory by analysing collected data. The consideration in inductive research is generally on the context in which events occur, focusing on small samples and qualitative methods (Saunder et al., 2007). The authors found the inductive approach fitting to answer the research questions due to several reasons:

1) As noted, the research topic was under-researched, while the related topics were comprehensive. The development of a theory itself which identified the intersections of the related topics was therefore the primary concern, and had to be done, prior to testing it deductively.
2) Due to the lack of literature on the subject as well as the limited data available, the inductive approach provided more flexibility and compatibility with more subjective data collection.
3) The exploratory nature of the research questions requires a clarification of the understanding of the problem. This is highly compatible with the bottom-up inductive reasoning.
4) The interest of the research client, i.e. Company X, was to gain in-depth knowledge of the research topic and a framework to apply for the pilot testing of their simulation endeavour. Thus, their inclination was aligned towards an inductive approach.

2.2 Research strategy

The research strategy was the plan on how the research questions were going to be answered. The choices made in the research design depended on the authors' preferences, the research philosophy, the research approach as well as the preferences of the research client. This section will explain and justify the research strategy choices made.

2.2.1 Relation with the research purpose

The research purpose was to gain new insights by assessing how performance measurement should be utilised for credible decision-support when evaluating simulations in manufacturing. The characteristics of the research purpose correspond with those of an *exploratory study.* The inherent lack of prior knowledge in the research field associated with an exploratory study requires flexible research design. The researcher(s) must be able to change the direction of the study when new data or insights occur (Saunder et al., 2007). As a result, the research design of this study was emergent in its nature, meaning that methods, questions and focus areas shifted throughout the research process. This was furthermore aligned with the pragmatic epistemological and ontological view.

2.2.2 Formulating a research strategy

The research strategy applied to this study was selected according to the research questions and objectives, the prior knowledge of the researchers, the resources available as well as the declared philosophical stand and research approach.

To begin with, the inductive approach implies theory building rather than theory testing, the research strategy for an inductive study should thus be aligned accordingly. The number of manufacturing organisations and people with knowledge of applying and evaluating simulation in manufacturing were furthermore, as earlier noted, sparse to the authors knowledge. This put a constraint on choosing an empirical research strategy which demanded a large sample size. Being an exploratory study further implied choosing a research strategy which would enable answering questions regarding "what", rather than "how" and "why". As an exploratory study requires a flexible design, it further called for a flexible research strategy.

Saunder et al. (2007) list three main ways of conducting exploratory studies:

1) a search of the literature;
2) interviewing "experts" in the subject; and
3) conducting focus group interviews.

Important to note is that research strategies are not necessarily mutually exclusive and can successfully be used in conjunction with each-other (Saunder et al., 2007). The chosen research strategy was congruent with the list by Saunder et al. (2007) and consisted of a case study, an interview study and an extensive literature review. The case study and interview study represented two sub-strategies which together was deemed the best way to answer the research questions. In the continuing part of section 2.2.2, a more detailed description and motivation of the chosen research strategy is provided.

Internal view: Case study

Fitting to the criteria of a fitting research strategy stated earlier was the case study. Case study strategies are often used in exploratory studies as they provides a good understanding of the research context and are useful for understanding organisational and managerial processes (Saunder et al., 2007, Yin, 2009). A case study can be defined by two technical characteristics, of which the first one is the scope:

1) The case study is an empirical enquiry that
   i) investigates a contemporary phenomenon in depth and within its real-life context; especially when
   ii) the boundaries between phenomenon and context are not clearly evident (Yin, 2009).

The second characteristic of the case study refers to the data collection and analysis strategies:

2) The case study enquiry:
   i) copes with the technically distinctive situation in which there will be many more variables of interest than data points; and as a result
   ii) relies on multiple sources of evidence, with data needing to converge in a triangulating fashion; and as another result
   iii) benefits from the prior development of theoretical propositions to guide data collection and analysis (Yin, 2009).

Regarding item 2.i) of the characteristics of a case study, the complexity of the research topic stemmed from the multiple aspects of the research questions. This was particularly the instance corresponding to the interconnected implications of the technical aspects of simulation, the design of performance measurement systems and the enabling of adequate decision support.

As discussed in the problem description in section 1.2, Company X was in the stage of implementing a DSS using simulation and was seeking a way to evaluate the simulations. The contextual situation of Company X was thus in essence the same as the phenomena which was to be investigated through the research questions. Furthermore, the research client, Company X, also provided the resources to conduct an in-depth investigation. Due to their unique current situation and availability, using Company X as a *holistic unit of analysis* in a *single case study* was therefore one fitting strategy to support answering the research questions.

The main available form of data at Company X was the experience and knowledge of individual employees. Using decision-makers and stakeholders relevant for the application of simulation-based decision support at Company X as the *units of observation* in the case study would cover the organisation's view of how the research questions should be answered with respect to:

1) their expectations of how a simulation-based decision support should be used;
2) where they see its usefulness in relation to their current practice; and
3) the evaluation of their historically occasional simulation projects.

The Company X employees' experience of simulation was however sparse and limited to the evaluation of presented results of outsourced simulations. The executed simulation projects were furthermore initiated with specific targets in focus and did not consider any general impacts nor the implications of continuous use of simulation. Hence, Company X lacked both the general knowledge of how performance measurement could be utilised for simulation-based decision support as well as experience of the effects of its implementation. This would however not cover all the variables of interest to answer both research questions, especially not *RQ1*. Furthermore, the data collected from Company X would provide an *internal view* that risked being:

1) *Company-specific*, i.e. not necessarily generalisable to other manufacturing companies,
2) *Factory-specific*, i.e. not necessarily generalisable to other factories, or
3) *Close-minded*, i.e. biased toward current practises, conformist and/or unreceptive to new ideas.

Theoretical view: Literature review

Regarding item 3.iii) on the characteristics of a case study, the prior development of a theoretical proposition is recommended to support the case study. Again, any literature on performance measurement for evaluation of manufacturing simulations was to authors' knowledge non-existent. In order to develop a theoretical proposition on the research topic, different topics related to it and their intersections had to be investigated to create an initial theoretical frame of reference.

However, to be useful as a basis for data collection and analysis in the study, the individual topics of the theoretical frame of reference further needed to be bridged and integrated into a theoretical framework. This theoretical framework would thus be an implied theoretical proposition, providing a starting point for the empirical research of the study. As a result, an emphasis on a more thorough literature review than typical for a case strategy was required to develop the theoretical proposition. this represented te theoretical view.

External view: Interview study

The authors found that data collection from a case study at Company X alone would not provide sufficient data to answer the research questions and ensure validity. Due to the theoretical and practical knowledge deficiency at Company X of designing and implementing performance evaluation of simulations, it was deemed necessary to complement the *internal view* case study.

The authors found that the pragmatic solution to complement the lacking data from the case study was to include an *external view* interview study. The interview study would include collecting data externally from experts in the field and other sources with knowledge and experience of performance measurement and decision-support on simulated manufacturing scenarios. The maintained that this additional data would be sufficient to fully complement the case study in answering the research questions. An interview study was furthermore fitting with the criteria and properties of an explorative and inductive study.

The overall strategy

While the *internal*, *theoretical* and *external view* represented individual substrategies for obtaining data and material to answer the research questions, how they were to be used conjointly to form an overall strategy is not answered. The authors argue that some conclusions could be drawn from analysing the intersections of related research topics in the theoretical view which would aid the analysis of the internal view. However, the conclusions and findings on the research topic would be richer and more valid if analysed in conjunction with data collected from the *external view.*

The strategy was therefore to first develop a conceptual analysis using the *theoretical* and *external view*, which would generate general findings. Thereafter, an empirical analysis was to be made which applied the general findings of the conceptual analysis with the data from the case study to make a practical analysis.

This two-phased approach would effectively triangulate and ensure validity of the study.

Summary

The research strategy was outlined by the development of the three major parts

1) *Internal view*
2) *External view*
3) *Theoretical view*

The *internal view* represented the basis of the single case study on Company X, and were as such the main part of the empirical study. The *external view* was the complementing interview study with *external view* experts, whose purpose was to fill the knowledge gap of Company X and to add validity to the study. Last, the theoretical view was in essence the theoretical framework constructed from the literature review, and served as the foundation for the data collection and analysis.

The overall research strategy, its components and interconnections are portrayed in figure 1.

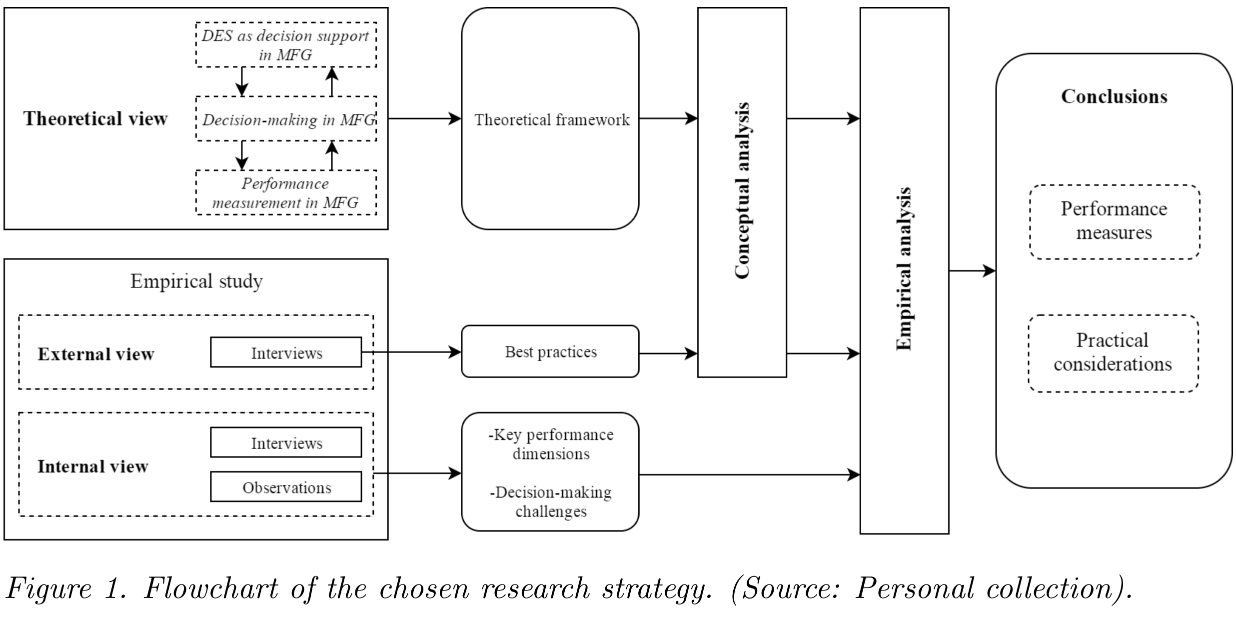

Figure 1. Flowchart of the chosen research strategy. (Source: Personal collection).

2.3 Research design

The research design was the plan how the chosen research strategy was going to implemented. As such, this section deals with the choice of data collection techniques and data analysis procedures. It describes and motivates the selection of research methods based on the previous research choices and the research questions.

2.3.1 Selection of research methods

The inductive research approach is traditionally associated with qualitative methods, although it is important to note that its not exclusively bounded to qualitative methods (Saunder et al., 2007, Creswell, 2014). Exploratory case studies further embrace both qualitative and quantitative methods (Yin, 2009, Saunder et al., 2007). Hence, the choice of method(s) was determined by the research questions and the resources available in terms of data.

Data collection techniques

As earlier noted, the main available form of data at Company X was the experience and knowledge of individual employees. Data collection from Company X was therefore required to be principally based upon interactions with these employees. A possible quantitative data collection technique for this purpose was conducting a survey. However, as discussed in section 2.2.2 about using a survey study as research strategy, a survey required a larger sample size than available at Company X to make any statistically significant inferences.

The same argument was valid for data collection from experts for the *external view*; the collectable data was in the form of experts knowledge and experience, and thus the survey would be most adequate among the quantitative techniques. Again, the availability of experts in performance evaluation of simulated manufacturing was sparse due to the lack of organisations with previous experience of it. Together with the lack of time to acquire a sufficient sample size despite the sparsity made the survey inadequate as a data collection technique for this study. Furthermore, quantitative research is in general characterised by more rigid and predetermined methods (Creswell, 2014). The close-ended questions of a survey fits that description, and is as such a poor fit for exploratory research such as this study. The overall conclusion was that quantitative data collection techniques were not appropriate, and that qualitative techniques would be more effective.

Internal view

In contrast with quantitative data collection techniques, qualitative research methods are generally more emergent and flexible than the quantitative (Saunder et al., 2007). Qualitative data collection techniques includes participant observation, qualitative interviews, as well as archival material such as documents and audio-visual material (Creswell, 2014, Saunder et al., 2007). Applicable to Company X were interviews and observations, as no organisational documents were retrievable for the authors. Interviews are commonly used in exploratory studies and case studies, and they are typically differentiated between structured interviews (i.e. questionnaires), semi-structured interviews, and unstructured interviews (Saunder et al., 2007, Yin, 2009).

Suitable for exploratory studies are interviews with open-ended questions such as semi-structured and unstructured interviews, as they provide the researcher with the possibility to probe answers so that the interviewees can build on and explain their responses. Furthermore, it enables the discussion to lead into topics not taken into account by the researchers, and can as such provide significant data with depth and detail to the study (Saunder et al., 2007). The difference between semi-structure and unstructured interviews is that the former is structured around predetermined themes and questions (although these are flexible between interviews and questions can both be omitted and added during interview). Unstructured interviews are on the other hand conducted more freely as the path of discussion is directed by the interviewee rather than the by the interviewer (Saunder et al., 2007). Due to the complexity of the research topic, containing multiple aspects, the authors found the semi-structured interview technique to be the most efficient in getting relevant data for answering the research questions.

As described under item 2.ii) in section 2.2.2 of the case study characteristics, using multiple sources of evidence in a case study to triangulate the variables of interest is highly pertinent. The second applicable data collection technique for the *internal view* was observations. Observations are useful for recording information as it occurs, noticing unusual aspects, and bring to light sensitive topics. Other advantages include the ability to gain firsthand knowledge and to notice aspects that might be overlooked by other data collection techniques (Creswell, 2014). Observations were made possible as Company X were willing to provide factory and corporate head-quarters visits. However, due to limited time and resources, the amount of visits and their duration was constrained. Observation was therefore regarded as a secondary source of data at Company X, in addition to the interviews. Moreover, as the process of simulating manufacturing scenarios had not yet been established, the process itself could not be observed. Rather, the authors saw the purpose of the observations in investigating the meaning that the employees attach to their actions.

External view

Considering the *external view* data collection, the authors recognised that the data would be mainly retrospective with respect to the experts' previous experiences and knowledge. As such, interviewing was regarded the best qualitative data collection technique to gain the additional insights necessary for answering the research questions. In comparison with the *internal view* population, the special characteristics of the *external view* population, i.e. more knowledgeable in the research topic, supported the more flexible unstructured interviewee technique. The view was that the more extensive knowledge of the *external view* interviewees would not require as much guidance. Unstructure interviews further enabled them to contribute more in-depth responses in their specific areas of expertise, providing richer data.

Data analysis procedures

The choice of data analysis procedure is dependent on what data collection technique is used as some data is harder to convert from quantitative to qualitative than others, and vice versa. To begin with, participant observations as well as semi-structured and unstructured interviews are all more compatible with qualitative analysis procedures (Creswell, 2014). However, the choice is foremost important to how the analysis supports answering the research questions. Regarding RQ1, the essence of the research question is investigating the relationship between performance measurement in the factory versus performance measuring on simulations. The conditions that refer to the situations are not strictly defined and highly contextual. The qualitative approach is more suitable than quantitative when taking a holistic account, and when developing a more complex picture of the problem using multiple perspectives (Creswell, 2014).

Continuing to RQ2; being a what-question, quantitative data analysis procedures such as statistical analysis might prima facie infer an answer to the research question. The qualitative data collected could in theory be translated into quantitative data on which statistical analysis is applied, e.g. the number of mentions of specific or types of performance measures in relation to an application are. However, as mentioned multiple times, for the answer to be statistically significant, it would have required a much larger sample size than was available with respect to both time and resources. Furthermore, the open-ended questions of the interviews is as noted poorly fitting for conversion to qualitative data. The authors' opinion was that using qualitative data analysis procedures, searching for themes and patterns in the responses of the interviews and observations, would be able to provide a valid answer for RQ2. Considering that the study is inductive and exploratory, the purpose was not finding definite answers, but rather building an initial theory on the research topic. Thus, qualitative data analysis procedures were deemed suitable for RQ2 as well.

Summary

The data collection techniques were chosen to be all qualitative. Data for the *internal view* was to be collected using semi-structured interviews as the prime data and observation with the role of participant as observer as second data. Data for the *external view* was on the other hand to be collected solely using unstructured interviews. Considering the data analysis procedure, they were chosen to be qualitative as well. The choices was made with respect to the research questions, the research approach and strategy, as well as the time and resources available. The research choice thus corresponds to a multi-method qualitative study.

The use of multiple methods is argued to be advantageous, as it allows better means to answer the research questions as well as data triangulation. Regarding the latter argument, its strength is that it mitigates the method effect, i.e. it decreases the effect on the results of specific weaknesses inherent in every technique and procedure (Saunder et al., 2007).

2.3.2 Time-horizon

A study can either be cross-sectional or longitudinal, i.e. either a study of a phenomenon or phenomena at a specific time or a study of the changes over a time-period. The choice of time-horizon is furthermore independent of both the research strategy and the choice of methods (Saunder et al., 2007). However, it is dependent on the time constraint of the study; as the thesis was to be written over the time period of one semester (roughly four months), the authors deemed that a cross-sectional study was more fitting to the study. This argument was strengthened by the authors' recognition that the literature review would be highly time consuming as well as that a longitudinal study would not yield better answers to the research questions.

2.4 Development of theoretical view

This section will describe the development of the theoretical view. It will start by describing how the literature collection for the theoretical view (chapter 3) was conducted; how literature material was searched for and how it was selected. Second, it will describe how the theoretical framework was developed based on the theoretical view.

2.4.1 Conducting the literature review

In the first step of developing the theoretical view, general key words and topics were identified from the preliminary research and the problem description provided by Company X. Based on the general key words, synonyms and related terms were identified and added to an extended list of key words. The key words were applied to search the Lund University Libraries' online search service for electronic and physical collections, i.e. *LUBsearch*, which is a collective entry point to all the libraries joint resources. Using different combinations of the key words, focus was on finding journals and books which were easy to obtain; being either available free online or physically at the Lund University libraries. The literature material was selected on the basis of evaluating its potential usefulness in answering the research questions. Further considerations in the selection of material were taken with respect to its quality, i.e. the reliability of authors and publications as well as the number of citations. The selected literature material was additionally used for backward and forward reference searching. This was done to circumvent the issue of relevant literature material being excluded from the key word searches, as well as to study the development of theories, follow up studies and expand the knowledge about the topics.

Theoretical frame of reference

The literature review was focused on three main topics which were identified as key aspects of the research topic from the preliminary research, the problem description, and research questions, i.e.:

1) DES as decision support in manufacturing applications;
2) decision-making and decision areas in manufacturing; and
3) performance measurement in manufacturing.

The focus was on finding theory in each of the topics which represented a comprehensive and grounded view of the research community. The theory presented either related to general themes of the three topics, important for building a thorough understanding, or especially, represented a high relevance to the research questions. The result of the literature review hence formed the theoretical frame of reference. A descriptive picture of the primary research topics are depicted in figure 2 below.

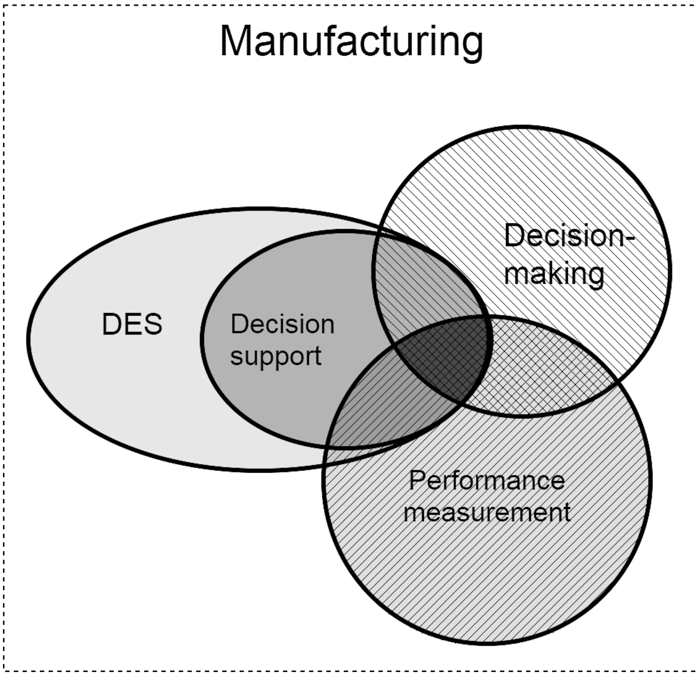

Figure 2. Research topics in literature review. (Source: Personal collection).

2.4.2 Constructing the theoretical framework

The theoretical framework was developed based on the theoretical frame of reference, particularly focusing on the interactions between the three main topics related to the research topic. In each of the topics, central issues relating to the research questions were identified and synthesised. Bridging of the central issues was done by investigating the points of contact between them and combining common themes. Formed on a distillation of the central issues and their interrelations, a canvas was developed which represented an integrated theoretical proposition of the research topic.

2.5 Data collection and sampling selection

This section will describe the aim and strategy of the data collection in greater detail. It will also present how the data collection techniques for the *internal* *view* and *external view* were applied in the study. First it will cover the semi-structured interviews followed by the participant observation for the *internal view*, and thereafter the unstructured interviews for the *external view* .

2.5.1 Internal view: Semi-structured interviews

Semi-structured interviews was the primary data collection technique for the *internal view.* This subsection will describe how the technique was applied in this study with respect to the interview questions, sampling and recording of the interview material.

Interview questions and structure

The interview questions consisted of a mix between:

1) *open questions* - to allow the interviewees to answer more freely and develop their response;
2) *probing questions* - to further explore important responses, provide explanations, and supplement open questions; and
3) *specific/closed questions* - to obtain specific information.

Although relative uniformity of questions were pursued in the interviews, flexibility was necessary due to the varying level of competence in different areas among the interviewees. Hence, both the questions themselves and how they were formulated varied among the interviews, and questions were subsequently also removed while others were added. The interviewees were further given some additional time to speak more freely on topics in which they had specific knowledge and interest, alongside with spontaneous probing questions. The interviews were in average conducted during one hour, covering 20 to 30 questions. An outline of the interview questions can be seen in appendix B.

Sampling

Interviewee candidates were selected with purposive criterion sampling on the basis of four profiles which represented the different types of key respondents for simulation-based decision support:

1) *Planning stakeholders*: Production planners or managers with operational and tactical responsibilities related to production planning;

2) *Investment decision stakeholders*: Mid and top-level managers with tactical and strategic responsibilities related to proposing and deciding on manufacturing investments;
3) *Manufacturing strategy stakeholders*: Top-level managers responsible for the implementation of the manufacturing strategy; and
4) *Continuous improvement stakeholders*: Advisers and decision-makers with responsibilities related to Lean or continuous improvement.

These profiles were however not necessarily exclusive, as one candidate could embody more than one profile in their role at the organisation. Moreover, the ambition was to sample diverse candidates with respect to Company X locations, e.g. candidates from multiple factories and the corporate head quarters to achieve heterogeneity. This was to ensure validity of a representative view for Company X, mitigating the risk of location-specific biased results.

Provided with the list of profiles, interviewee candidates were recommended by the supervisor at Company X. Although some control of the sampling was consequently lost, given the size of Company X, the filtration by the supervisor was deemed necessary to find knowledgeable and willing interviewees. The supervisor at Company X further initiated the contact with the candidates, introducing the authors and asking for their participation in the study. Interviews were thereafter booked with the accepting candidates, who were also briefed with an agenda and information about the topics of the interview.

In total, eight interview sessions with ten employees at Company X were conducted [1]. A list of all the *internal view* interviews, with details including their corresponding reference code, can be seen listed in table A1 in appendix A.

Recording the interviews

The authors' ambition was to conduct interview face-to-face as far as possible, meeting the informants in person. However, as the factory locations of Company X are scattered all over Europe, there were not resources nor time to accomplish that. Instead, the interviews which could not be conducted in relative proximity to Lund, i.e. outside the vicinity of Sweden, were conducted through videoconference calls.

Records of all the *internal view* interviews were made by audio-recording both face-to-face and videoconference call interviews with the permissions of the infor-

[1] Two interview sessions were conducted with groups of two interviewees

mants. Audio-recording was used due to several advantages, e.g.:

1) allowing better concentration on both questioning and listening, as no focus had to be directed at keeping up with taking notes;
2) providing an accurate and unbiased recording of the interviews, further enabling direct quotes to be used;
3) making it possible to re-listen the interviews, ensuring that no information was missed; and
4) perceiving intonations and emphasis of the responses, capturing the tone of voice (Saunder et al., 2007).

2.5.2 Internal view: Participant observation

Participant observation was the secondary data collection technique for the *internal view*. This subsection will detail how the observations were carried out, what data was recorded and how it was done.

Participant observations can be categorised by the researcher's role during the observations: complete participant, complete observer, observer-as-participant, and participant-as-observer (Saunder et al., 2007). The role most fitting to this study was observer-as-participant, i.e. as a spectator where the purpose of the researcher's presence is known to the observed. The choice was made based on the presumption that there was no risk of the research subjects being defensive knowing the research purpose, and that it was not possible for the authors to take part in the activities.

The observations were unstructured; data was collected when material relevant to the research topic was observed. They were also done in a naturalistic setting, at Company X locations. Alongside with reoccurring meetings with the Company X supervisor at the corporate head-quarters, the main source of observational data was through a two-day visit at Factory 1. The visit included a whole-day meeting with, among others, the elected key user of the simulation-based tool (i.e. Planning Manager at Factory 1 and representatives from the simulation development consultancy firm.

The data was recorded primarily in real-time by taking notes during participation in meetings and informal discussions. However, compilation of observations were occasionally done post hoc. Questions to the informants during observation included clarification of what had been observed by the authors as well as of the accounts of circumstances described by the informants.

2.5.3 External view: Unstructured interviews

Unstructured interviews was the sole data collection technique for the *external view*. This subsection will describe how the questioning, the sampling as well as the recording of the *external view* interviews was handled in the study.

Interview questions and structure

Compared to the *internal view* semi-structured interviews, the *external view* unstructured interviews were much less directed in terms of listed questions. Although some questions asked were indeed similar to those of the *internal view* interviews, they were not predetermined. Furthermore, rather than asking any closed questions, the questions were either open or probing with the purpose of supplementing the open questions. The loose structure of the *external view* interviews was driven by the absence of direction. The interviews were held within the frame of relevance of the research topic, albeit, the emphasis and time spent on different subtopics were largely dictated by the informants. The purpose of this structure was letting the informants develop their responses in the areas of their respective expertise to enrich the data. Similar to the *internal view* interviews, the *external view* interviews were held during one hour. The number of questions were however highly flexible, highly varying among the interviews.

Sampling

The population of experts in performance evaluation of manufacturing simulations was to the authors knowledge sparse due to the lack of research in the topic as well as the limited implementation in manufacturing organisations. Purposive sampling was used to find suitable interviewees from the small population. The criteria for the sampling was that the participators either had theoretical or practical experience of developing, implementing and evaluating production simulations. The ambition was also to achieve heterogeneity in terms of occupation.

The sample consisted of four participators; a detailed list of the *external view* interviews conducted can be seen listed in table A2 in appendix A.

Recording the interviews

The majority of the *external view*interviews were conducted face-to-face. Like the *internal view* interviews, and for the same reasons as listed in subsection 2.5.1, half of the *external view* interviews were audio-recorded. However, the other half was recorded in real-time on paper by the authors.

2.6 Data analysis

This section will describe the data analysis procedures. First it will explain how the raw data was prepared for analysis. Thereafter, the section will cover the data analysis strategy and explain and motivate all the steps of the analysis.

2.6.1 Preparation for data analysis

Before the data could be analysed, the raw data needed to be processed and prepared. This included transcription of audio-recorded interviews and translation of data. How this was proceeded will be described below.

Transcription

A majority of the interviews were audio-recorded. Subsequently, they had to be transcribed into written accounts before being analysed. The transcription was made by the authors through data sampling, i.e. only the parts important for the study were transcribed. Data sampling was chosen due to the open-ended questions of both the *internal view* and *external view* interviews. In the same way as the open-ended questions enriched the data by producing developed and thorough responses, they also resulted in segments of data irrelevant for the study. Moreover, full account transcriptions without the use of voice-recognition software or a professional typist are immensely time-consuming (Saunder et al., 2007). Hence, data sampling also enabled faster transcription processes.

Translation

While half of all the interviews were held in English, the rest were held in Swedish. The interviews in Swedish were hence translated to English by the authors post transcribing the material.

2.6.2 Data analysis strategy

The purpose of qualitative data analysis procedures is identifying themes and patterns in the complex set of qualitative data generated through interviews and observations (Saunder et al., 2007). Moreover, case studies rely on analytic generalisation, by expanding and generalising theories (Yin, 2009). To facilitate this, the data was analysed according to the following steps:

1) categorisation;
2) unitisation;
3) patterns and themes analysis; and
4) theory development

In addition to the theoretical view developed from literature, the research strategy was to first formulate an *internal view* and *external view* before developing a theory. To develop these views, the data collected corresponding to them needed to be treated separately. The two empirical views were formulated using steps 1), 2), and 3). After the empirical views had been formulated, it was followed by the process of theory development. This was done in two steps: First, a conceptual analysis was done by combining the findings from the *theoretical view* with those from the *external view*. Second, an empirical analysis was done by using the conceptual analysis and applying it with the *internal view*. How the data analysis was proceeded in each step will be described in detail below.

Categorisation

The first step of the data analysis was to categorise the data into meaningful parts which could be systematically analysed. In addition to supporting the management of the data, the categorisation helped with integrating data from different sources and identifying patterns and themes. In turn, this aided the development of theory and drawing of conclusions from the collected data.

Categorising the empirical views

The categorisation of the data corresponding to the *internal view* and *external view* respectively was done independently, although, the categorisation procedure was the same in for both sets of data. The *internal view* represented a holistic single case study, hence, the multiple perspectives needed be integrated and analysed in conjunction. As a result, next to the interviews, the observations were treated as another perspective of the *internal view*.

While there are multiple different strategies to categorising data, the authors chose to adopt an inductive analysis strategy. The categories were hence derived from the data rather than from the theory and theoretical framework. However, as the interview questions themselves were to some degree a product of theory, its relevance to the data collected, and thus the categories, was not omitted. This strategy was chosen due to its suitability for exploratory studies, in which theory emerges from the data. Furthermore, as there was limited previous research on the topic and the theoretical framework was a product of analysis of relating theory, a deductive analysis strategy might have been restrictive and not representative of the participants' views.

The categorisation closely resembled the procedure known as template analysis (Saunder et al., 2007). The initial step of the categorisation was to derive general topics from the transcripts of each interview and observation notes. All topics were then arranged into a list of topics, where the occurrence of each topic was counted. This procedure provided a structure for analysing the weight of each topic in terms of collected data. Based on their weights, a hierarchy of the topics were constructed. Topics of high occurrence were set as self-supporting categories and subsequently broken down into subcategories. Topics of low occurrence were set as subcategories merged into either new subcategories/categories and/or linked to a preexisting category depending on their relevance to each other. As such, the categories were descriptive in their nature, representing the responses and observations.

Unitisation

Unitisation was the second step of data analysis, and its purpose was to attach bits of data, i.e. units, to the chosen categories. Guided by the research questions, it is a process of selecting relevant data and rearranging it into a more manageable form (Saunder et al., 2007). Due to it being a selection process, it was simultaneously a process of data reduction; data which is deemed irrelevant for answering the research questions are subsequently discarded at this step. The unitisation was made by iterating over the data and copying relevant bits to a separate document for each category. Thus, the documents became containers with unstructured units of data relevant for the specific category. To keep track of the data source of each input, they were all labelled accordingly.

Patterns and themes analysis

Based on the documents of data units corresponding to the different categories, the individual units were analysed looking for similarities and discrepancies between the sources. This step was characterised by interpretation by the authors as similar claims and opinions could be expressed in different terms. At the same time, consideration had to be taken to not lose important nuances from the individual sources when unifying views into themes.

2.6.3 Theory development

As noted, theory was developed in two separate phases. The theory development was made based on the analysis of the collected data and literature, as well as by discussion including the authors' own view and knowledge on the subjects.

Regarding the first phase, the conceptual analysis, it had its basis in the *external view*. By going through the different themes formulated in the *external view*, corresponding subjects were related to the *theoretical view*. By structurally analysing the combined material, theory was formed trough conceptualisation. The first phase represented the general findings on the research topic and aimed to answer RQ1 and RQ2 partially. In the second phase of doing the empirical analysis, the concepts developed in the first phase were applied and used together with the *internal view*. The second phase was characterised by a more practical approach, aiming on fully answering RQ2 and formulating a concrete proposal for the implementation of simulation-based decision-support at Company X.

2.7 Research limitations

The three areas covered by the literature review, i.e. decision-making in manufacturing, DES as decision-support, and performance measurement, are all well-researched fields. Due to the vast amount of research done, the time-frame of writing this thesis forced limitations on what could be covered. Thus, the authors acknowledge that potentially relevant material to this study might have been missed or disregarded. The authors do however believe that the most relevant areas was coverd.

The key limitation to the research was to find a sufficient level of sample data for the empirical view. This was the case both internally, regarding interviewees at Company X, and the number of external companies participating. The issue with insufficient sample data is partly that it might produce a biased result, but also that the data collected might miss aspects and considerations of importance. The number of companies implementing simulation as decision-support in manufacturing is very limited. In Sweden, there was only one company to the authors' knowledge which continuously implemented simulation-based decision-support.

The number of interviewees at Company X was limited due to the time-frame of writing this thesis as well as a problems with cooperativeness. The latter is inter alia due to a history of problems with technology acceptance, decreasing possible candidates' willingness to participate in a simulation implementation project. The technology acceptance issue also led to the corporate headquarters wanting to be cautious with spreading the news of simulation implementation before a successful role-out at Factory 1 was accomplished. While simulation as decision-support had previously been implemented in project form at some factories, the development of the simulations had been outsourced to external consultancy firms. Therefore, the overall experience and understanding of simulation in the organisation was generally low.

Moreover, Company X suffered from silo-thinking at the factories as well a suspicion towards projects initiated by the corporate headquarters. As this was the case with the simulation-based decision-support, this also limited the list of possible interviewee candidates. To mitigate the effects of limited number interviewees at Company X, an extra emphasis on finding broad and differentiated sample was made, with respect to both location and manager level. Although this might have caused inadequate representation of manager level and location-specific views, it better encapsulates the generic view of Company X. Furthermore, while not being fully representative for manager level and location-specific views, the specific aspects are at least covered. Following, this required a more sceptical view towards outlying opinions and stated facts from the interviewees at Company X.

2.8 Quality of the study

In this section, the quality of the study will be discussed in terms of credibility, validity and reliability. However, they will not be addressed individually but discussed in general form.

The implications on reliability of being an inductive and exploratory study was that the focus was not predefined more than in the form of the research purpose, research questions and objective. The orientation of how the research questions were going to be answered progressed evolutionarily during the research process. The reliability of the study was potentially impacted by that consideration needed to be taken into providing the research client (i.e. Company X) with a valuable output. However, it should be noted that other than a research proposal, no directions were given on the proceedings of the research throughout the process.

The credibility and validity of the study was strengthened by the use of multiple methods of data collection, i.e. method triangulation. For the *internal view*, both semi-structured interviews and participant observation was applied, and for the *external view* semi-structured interviews were used. Together with the *theoretical view*, the different sources ensured a higher credibility of the study.

To better reflect the view of the interviewees, the data was audio-recorded so that what data collected was not contaminated by any bias of the authors. Furthermore, it enabled to preserve not only *what* the interviews said in exact detail, but also *how* they responded, thus capturing what they emphasised and not. However, the transcribed data was sampled from the recordings, which posed a risk of unintentionally filtering out data which was of importance. To mitigate the risk of missing important data, the transcripts were sent to the corresponding interviewees for checking and confirmation of their accuracy. Objectivity was further striven for in the data analysis. However, the authors acknowledge that the data analysis was inevitably coloured by the views of the authors during both data processing and the themes and patterns analysis.

While the topics of the interviews were predefined, both the semi-structured interviews and unstructured interviews were mainly conducted using open-ended questions. As such, the authors influence on the the interviewees' answer was very limited. Among the *internal view* interviewees, there were a few who were stakeholders in Company X's simulation endeavour. This might have impacted on their answers, potentially downplaying potential problems and issues relating to simulation. There was a potential bias in the sampling of interviewees at Company X as the sampling was done indirectly via the supervisor at Company X. The supervisor was further highly involved in the simulation endeavour and had a relation to the interviewees. As such, the interviewee responses might have been influenced by subject bias.

While the study was conducted as a single case study, a significant portion of the study was dedicated towards reaching general findings by performing a conceptual analysis on the research topic. The general findings are highly transferable to any study involving performance measurement, decision-support and simulation. Moreover, the specific findings from the unit of analysis in the empirical analysis are generalisable for any manufacturing organisation in similar situations.

Chapter 3

Theoretical view

In this chapter, research and earlier work related to the topic of this study are reviewed and a theoretical framework developed. Concepts, frameworks, theories, and models are presented, and accompanied with a discussion on their relation to this study. Due to the vast amount of research in the area, the literature review will be focused on selected research most relevant to this study.

The first section discusses decision-making, focusing on establishing the concept of knowledge-based decision-making and theory on decision-making in manufacturing specifically. The next section covers performance measurement in manufacturing, including defining manufacturing performance and discussing how performance measurement should be both structured and applied. In the third section, discrete event simulation and decision support systems are described. Last, a theoretical framework is developed based on combining parts of the key concepts of the previous sections.

3.1 Decision-making

Bennet & Bennet (2008, p. 4) argue that making a decision involves several components and state the following:

> *"Every decision has hidden within it a guess about the future. When solving a problem, or achieving a goal, we estimate the situation and then anticipate that if we take a certain action (or series of actions), another situation will be created which will achieve our desired objective."*

In other words, the main components of a decision are:

1) an understanding or interpretation of the current situation
2) a desired new situation (or outcome), which the objective is to achieve
3) an idea about what actions to take in order to realise the desired outcome

In complex situations and environments, which are increasingly common in today's world, decision-makers turn to their intuition and judgment. However, one can argue that intelligent and informed decision-making is more relevant than ever (Bennet & Bennet, 2008).

3.1.1 Knowledge-based decision-making

Holsapple (2008) regards decision-making as an activity based on knowledge, which is the key to supporting better decisions. It can be seen as a process in which knowledge is both input and output, "Work in process" and subcomponents, while at the same time forming the context in which the decision is made. Using the analogy of a manufacturing system, the decision-making process on a conceptual level is described as one which requires knowledge as input and produces new knowledge as output, while the process itself is one of transforming knowledge. His knowledge-based conception of decision-making is described in figure 3 below.

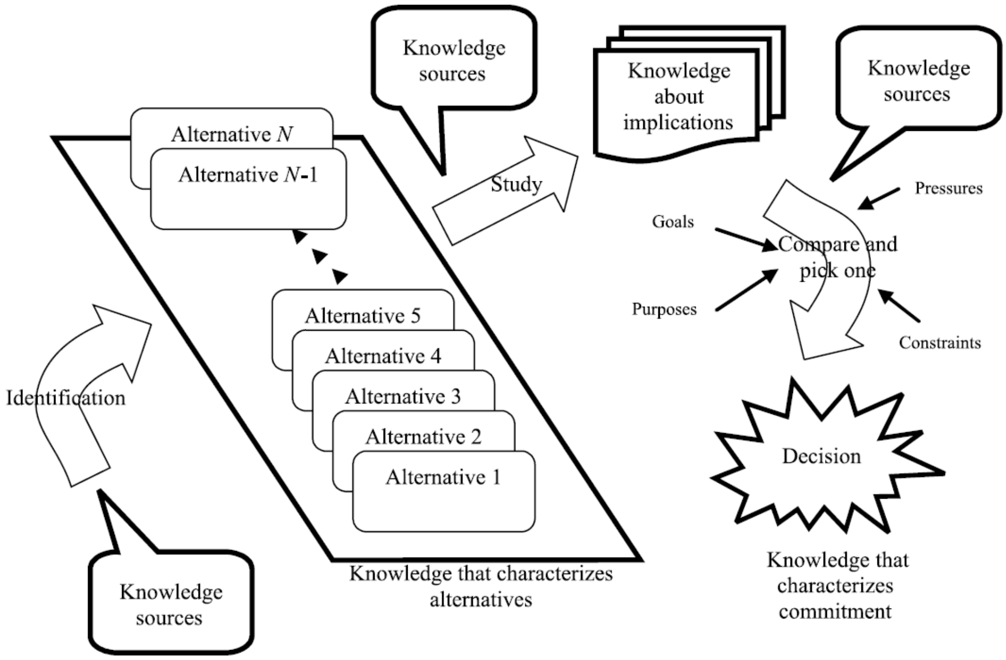

Figure 3. Knowledge-based conception of decision making. (Holsapple, 2008).

The first step of decision-making in figure 3 is to identify an (arbitrarily large) set of alternatives. Then, one selects, studies and evaluates the implications of some or all of them, to a reasonable extent. Lastly, they are compared on the basis of purpose, goals, pressures and constraints, in order to finally pick one and arrive at a decision.

Given the knowledge-based conception of decision-making, the question arises how to define knowledge in this context, how it is created and how that process interacts with the actual decision-making. Holsapple (2008) interrelates three basic phases of decision-making, *Intelligence*, *Design* and *Choice* (originally by Simon (1960)), with the six *knowledge states* identified by Van Lohuizen (1986).

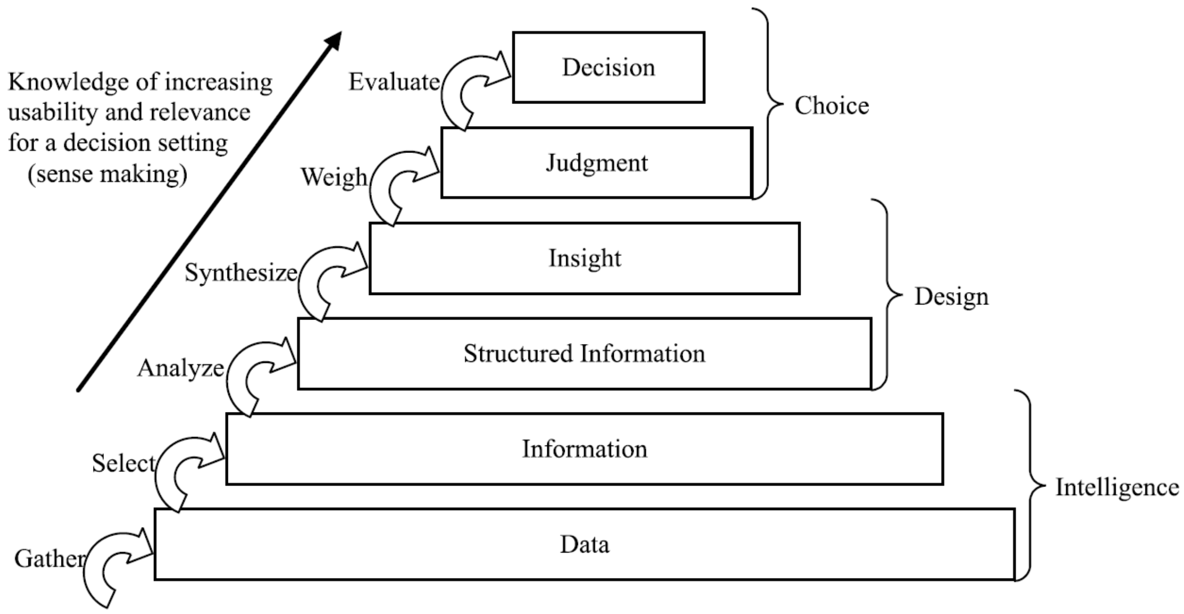

Figure 4. Knowledge as a progression of states. Adapted from Holsapple (2008), based on Simon (1960), Van Lohuizen (1986))

Figure 4 shows how Information created by selecting from Data gathered, which corresponds to the Intelligence phase of decision-making. In this phase, the decision-maker is concerned with finding what to make decisions about, diagnosing and relating data or information to the organisational objectives. The information is analysed to produce Structured Information, which in turn is synthesised into Insight in the Design phase. The design phase involves considering which courses of action that would be appropriate to resolve the issue at hand. The insight is then weighed, leading to a Judgment about it in the Choice phase. Finally, the judgment is evaluated and a decision can be made. Thus, the Choice phase is where the decision-maker will select one alternative over others, based on his/her knowledge about them, or discard them all and return to the Design phase. Overlooking the terminology, the main idea of figure 4 can be summarised as that through processing activities, knowledge progresses from lower states of low or unclear usability for the decision-maker, to higher ones with increasing relevance.

Information overload

The information needed for decision making has been under much research. Due to the vast amount of data available from a simulation model, consideration into the volume of information that a decision support system should supply must be taken. This has brought the concept of *information overload* into the spotlight. Pijpers (2010) explains the basis of the concept being that the value of additional information only increases as the recipient is able to process it. Consequently, there will be a limit when the amount of information input to the recipient exceeds his processing capacity - this is when information overload occurs (Pijpers, 2010, Speier et al., 1999). As the cognitive capacity of decision-makers, like everybody else's, is not unlimited, the information overload will have a negative impact on the decision quality (Speier et al., 1999). Referring to multiple studies in different disciplines, Speier et al. (1999) claims that information overload caused increased confusion about the decision and increased the time to make it.

3.1.2 Decision-making in manufacturing

The *manufacturing competitive priorities* (MCP) [1] of manufacturing organisation constitute classes of attributes which are important for decision-making (Chryssolouris, 2006). The decisions made on the decision areas (described in section 3.1.3) with respect to the MCP encapsulates the manufacturing strategy (Leong et al., 1990) (see figure 5). All objectives, goals and criteria[2] of a manufacturing strategy can be described relating to the attributes of the MCP (Chryssolouris, 2006). It should however be noted that the relations between the attributes and the MCP is not always straightforward, and a successful identification of these would improve decisions (Rusjan, 2005).

Decisions should be made with respect to relative importance of the MCP in order to support the manufacturing strategy. However, while different MCP are assigned with different levels of importance with respect to the manufacturing strat-

[1] A deeper explanation of different competitive priorities is provided in section 3.2.2.

[2] Chryssolouris (2006, p. 9) defines an objective as an attribute to be minimised or maximised, a goal as a "target value or range of values for an attribute", and a criterion as "an attribute that is evaluated during the process of making a decision".

egy, decisions should not solely focus on the competitive priority with the highest importance. Decisions should rather be made with respect to the difference between the desired (as determined by the business strategy) and the achieved performance relating to the different MCP (Rusjan, 2005). Hence, decisions should be problem-based; not only taking into account the importance of a specific competitive priority, but also the importance of the problem (i.e. the discrepancy between desired and achieved performance) relating to a competitive priority (Rusjan, 2005).

Naturally, the MCP are all interrelated, and the outcome of a decision on an attribute has in general trade-offs on other attributes. Traditional examples of this are cost-quality and dependability-flexibility (Leong et al., 1990). As a result, it is in practice impossible to simultaneously optimise all classes. The essence of decision-making has therefore historically largely revolved around the assessment of trade-offs (Rudberg, 2002, Chryssolouris, 2006). However this view has been challenged. For instance, the emergence of lean and Toyota Production System (TPS) showed that there does not necessarily have to be a trade-off between cost and quality, but that the real issue is finding techniques that improves quality and total cost (Leong et al., 1990).

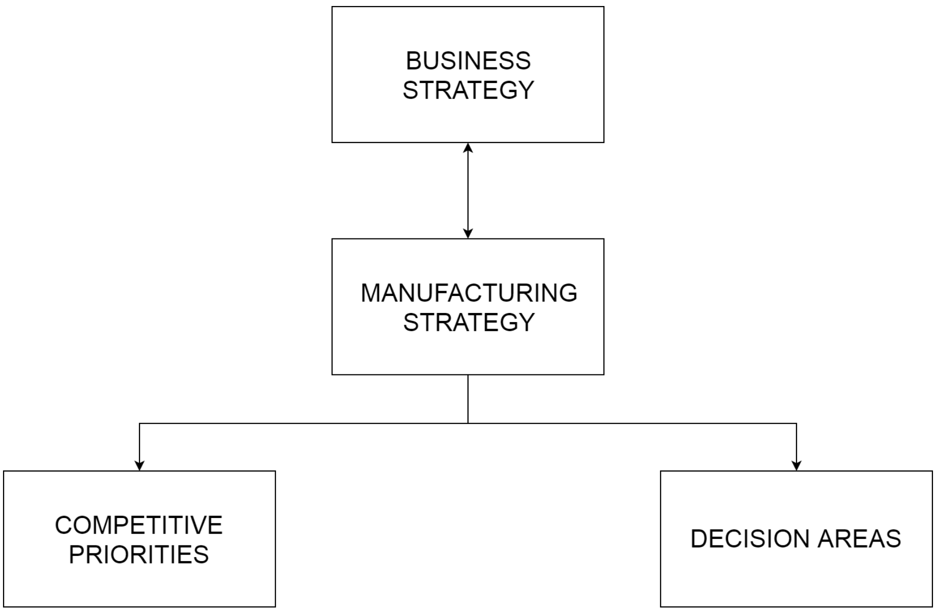

Figure 5. Predominant content model of manufacturing strategy. Based on Leong et al. (1990).

Chryssolouris (2006) argues that the decision-making process is formed on the performance objectives, goals or criteria of relevant manufacturing attributes. Connected to every decision are decision variables related either to the design or to the operation of a manufacturing process, machine or system. The decision variables can be generally defined as the variables which the decision maker can change. It follows that every decision in manufacturing can be seen as the selection of values on decision variables which affect the attributes. Furthermore, the decision making process can be seen as "a mapping from desired attribute values onto corresponding decision variable values" (Chryssolouris, 2006, p. 11).

3.1.3 Decision categorisation

This section will discuss how decision in manufacturing can be categorised. First, the concept of (strategic) decision areas is briefly introduced. Thereafter, the relation between manufacturing decisions and managerial decision levels will be covered.

Strategic decision areas

The manufacturing strategy is the pattern of coordinated decisions which impact the ability of the manufacturing function to meet business strategy goals and the manufacturing task (Leong et al., 1990). Therefore, the decisions made in manufacturing constitute a link between the business strategy and the manufacturing operations (Ward et al., 2007). The strategic decisions can be categorised into different areas which are constituents of the system with long-term importance for the manufacturing function (Leong et al., 1990, Choudhari et al., 2010). The *decision areas* are in essence a breakdown of the manufacturing strategy, and as such, they represent the manufacturing organisation's structure and capabilities (Rudberg, 2002, Ward et al., 2007). Following, the strategic decisions made in the decision areas determine internal composition and configuration of the manufacturing system.

The decisions areas can furthermore be categorised into being structural or infrastructural (Wheelwright, 1984). Structural decision areas are strategic in nature with long-term impacts on the manufacturing organisation and large capital investments, and can be describe as being the "bricks and mortar decisions of capital spending" (Leong et al., 1990, p. 114). The infrastructural decision areas are more tactical and on-going decisions with individually lower capital investments. These decisions are linked to operational aspects and "affect the people and systems that make manufacturing work" (Leong et al., 1990, p. 114). The decision areas themselves vary from author to author, however, they have significant overlaps and the differences are in general the adding and removal of some decision areas. The perhaps most cited framework of decision categories were suggested by Hayes &

Wheelwright (1984) and can be seen in table 1.

What the appropriate decisions are regarding performance improvement on a specific competitive priority is not generic, but is dependent on the configuration with respect to the decision areas.

Table 1. Strategic decision categories in manufacturing. Adapted from Leong et al. (1990) and Rudberg (2002), based on Hayes & Wheelwright (1984).

Decision Category	Sample of policy areas
Structural	
Capacity	Amount, timing, type
Facilities	Size, location, focus
Vertical integration	Direction, extent, balance
Technology	Equipment, automation, connectedness
Infrastructural	
Production planning and control	Computerisation, centralisation, decision rules
Quality	Defect prevention, monitoring, intervention
Organisation	Structure, reporting levels, support groups
Workforce	Skill level, pay, security
New product development	

Decision levels

Besides the decision areas, decisions can be categorised into three levels: strategic, tactical and operational. These levels correspond to the decision's application, its impact on different levels of management, as well as the time horizon of the activity (Gunasekaran et al., 2004, Rudberg, 2002). There exist a limit to the amount of information a decision-maker can consider, which is proportional to the planning time-horizon. The product of the time horizon and the volume and detail of information should therefore optimally remain constant. As a consequence, the longer the time-horizon of the decision, the smaller the volume and less detailed the information should be (Rudberg, 2002). In table 2, the characteristics of decisions with respect to the different levels are described in detail.

Table 2. Characteristics of different level decisions in manufacturing. Adapted from Silver et al. (1998).

Category of decision	**Strategic**	**Tactical**	**Operational**
General types of decisions	Plans for acquisition of resource	Plans for utilisation of resources	Detailed execution of schedules
Managerial level	Top	Middle	Low
Time-horizon	Long (2+ years)	6 to 24 months	Short range
Level of detail	Very aggregated	Aggregated	Very detailed
Degree of uncertainty	High	Medium	Low
Examples of decision variables	• Products to sell • On which dimensions to compete • Sizes and location of facilities • Nature of resources • Labour skills • Nature of production planning • Inventory management decisions systems	• Operation hours of plants • Work force sizes • Inventory levels • Subcontracting levels • Output rates • Transportation modes used	• What/when to produce • On what machine to produce • In what quantity to produce • In what order to produce • Order processing and follow up • Material control

3.1.4 Conclusions

Decisions in manufacturing can be broken down into four structural and five infrastructural decision areas. The decisions made on these decision areas with respect to the MCP forms the manufacturing strategy. Depending on the time-horizon, decisions can further be categorised as either strategic, tactical or operational. These decision categories are associated with different characteristics, such as types of decisions and aggregation levels of information detail and volume. The manufacturing decision itself can be seen as the selection of values decision variables corresponding to some relevant attributes of the MCP. Hence, the decision-making process can be described as the mapping of attributes onto decision variable values. Supporting the manufacturing strategy, strategic decisions should be made with respect to the MCP and their relative importance.

3.2 Manufacturing performance measurement

In a literature-study by Gunasekaran et al. (2004), measuring the performance of SCM is identified as key for an efficient and effective supply chain. As a representation of reality, this is equally true for an effective simulation-based decison support; the performance of simulated scenarios in manufacturing must be measured. Melnyk et al. (2004) identifies the need for measuring performance to be:

1) *Data refinement.* Increasing data volumes through greater span of control and growing complexity of operations, makes data management increasingly difficult.
2) *Data distilling and information enriching* Operations need these functions to operate effectively and efficiently on a day-to-day basis.
3) *Decision-support* The action and decisions determine the degree and nature of value that an operation creates. These actions and decisions can be greatly influenced by PMs. (p. 211).

Moreover, the general purpose or function of measuring performance can roughly be summarised to:

1) identify success;
2) identify whether customer needs are met;
3) help the organisation to understand its processes and to confirm what they know or reveal what they do not know;
4) identify where problems, bottlenecks, waste, etc. exist and where improvements are necessary;
5) ensure decisions are based on facts, not on supposition, emotion, faith or intuition; and
6) show if improvements planned, actually happened (Parker, 2000).

Since the 1990s, there has been a vast amount of research on performance measurement in general. Much of the research deals with performance measure (PM) frameworks, performance measurement system (PMS) design, and with the impact of implementing PMSs in an organisation. Notably, in the last 10 years, much of the research has been focused on more distinctive applications such as integrating sustainability and "green measures" into PMSs. A unified definition of performance measurement is hard to find. Neely et al. (1995) describe performance measurement as the process of quantifying action, and identify two dimensions of performance; *effectiveness* and *efficiency.* They define effectiveness as a measure of how well customer requirements are met, and efficiency as a measure of how economically the organisation's resources are utilised with respect to the given effectiveness. On this foundation, the following concepts are defined:

1) *Performance measurement* - the process of quantifying the efficiency and effectiveness of action;
2) *Performance measure* (PM) - a metric used to quantify the efficiency and/or effectiveness of an action; and
3) *Performance measurement system* (PMS) - the set of metrics used to quantify both the efficiency and effectiveness of actions (Neely et al., 1995).

There exists much terminological confusion in performance measurement research, and definitions vary from author to author. However, for consistency and readability, the continuing discussion on performance measuring will be based on the above definitions by Neely et al. (1995). Hence, when referencing literature using other definitions of concepts, e.g. metrics instead of performance measures, they will be translated into the above definitions.

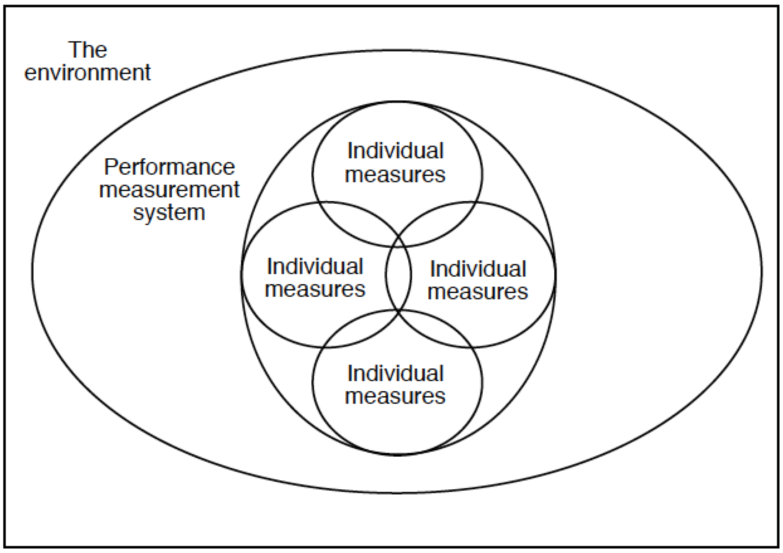

Figure 6. Analytic layers of a PMS. (Neely et al., 1995).

The dimensions of performance described by Neely et al. (1995) accentuate that both external and internal arguments motivates action. This is an important observation since it implies that PMSs must take a holistic view of the value chain into consideration to capture both external and internal factors.

A PMS can be studied at three levels (see figure 6), i.e.:

1) the individual performance measures;
2) the set of performance measures - the performance measurement system as an entity; and
3) the relationship between the performance measurement system and the envi-

ronment within which it operates (Neely et al., 1995).

In the following part of section 3.2, the key aspects of performance in manufacturing will be reviewed. Thereafter, the PMS will be studied according to the three levels described by Neely et al. (1995).

3.2.1 The performance pyramid

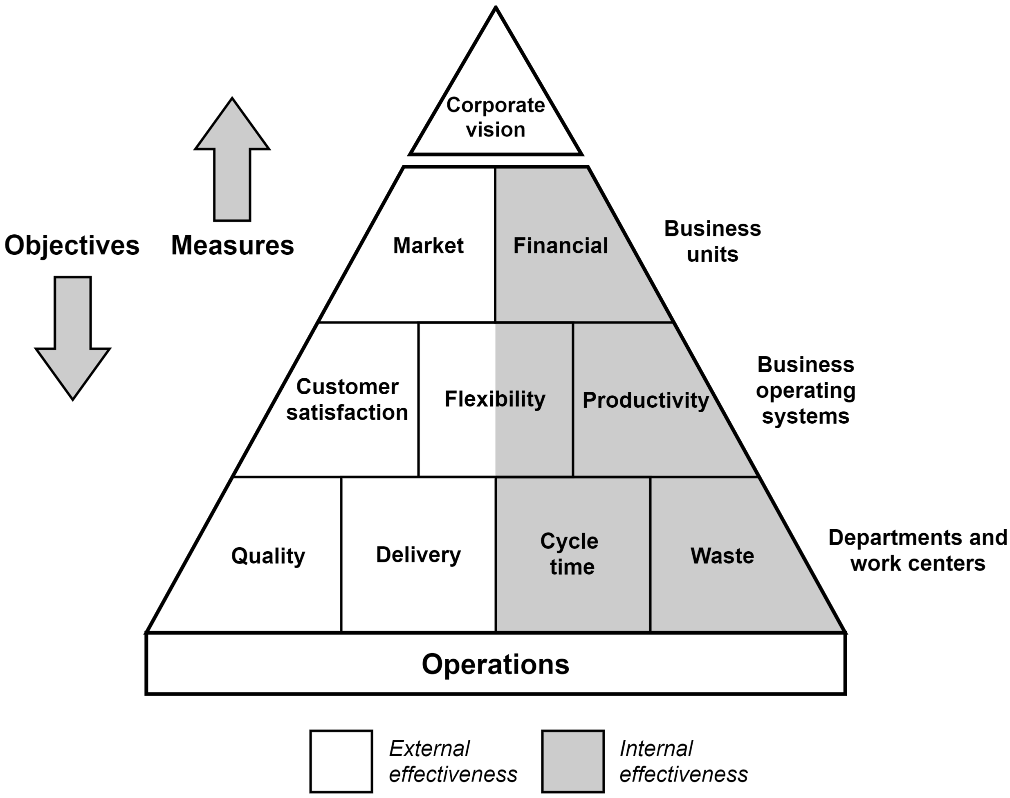

Figure 7. The performance pyramid. Adapted from Cross & Lynch (1992).

The organisational hierarchy of manufacturing performance areas as well as their relationship to internal/external effectiveness, can be studied in the performance pyramid proposed by Cross & Lynch (1992) (see figure 7). The performance pyramid shows the aggregation of performance measures upwards in the manufacturing organisation, and the disaggregation of objectives downwards. Like in the content model for manufacturing strategy in figure 5, the corporate vision (or strategy) is at the top level, determining where and how to compete. At the second level are business units (e.g. factories), which encapsulates the companies' key results, objectives and measures. Business units' performance are determined by their ability to achieve short-term financial targets and long-term growth and market position targets (Cross & Lynch, 1992). The third level, business operation system, includes all internal functions and activities with the objective to develop, produce and distribute products effectively and efficiently (Cross & Lynch, 1992). Their performance is measured by the customer satisfaction, flexibility and productivity. At the bottom level are the drivers of performance, according to Cross & Lynch (1992). They are directly connected to the operational day-to-day activities, and the objective and goals on these areas affect the whole organisational performance. Moreover, as the performance pyramid visually demonstrates, performance measurement is key in translating the corporate vision to reality (Melnyk et al., 2004).

3.2.2 Manufacturing competitive priorities

The performance pyramid proposed by Cross & Lynch (1992) provide a comprehensive view of the interrelations of manufacturing performance. However, from a strategic perspective, manufacturing performance is usually described by the manufacturing system's performance on a collection of MCP. These are performance areas which are defined by a consistent set of goals for manufacturing (Leong et al., 1990). It has been shown that there is a positive correlation between the performance on the MCP and the business performance. Thus, manufacturing performance should be measured by the results concerning the MCP (Rusjan, 2005). While the manufacturing capability concern the potential performance, MCP concern the performance important for achieving competitive advantage (Choudhari et al., 2010). However, the capabilities should be matched with the MCP in order to achieve environmental fit.

The MCP of the manufacturing system and their relative importance is determined by the business strategy, and thus vary across industries and corporations (Rusjan, 2005). Literature usually consider five MCP: cost, quality, delivery, flexibility, and innovativeness (Leong et al., 1990, Miltenburg, 1995)(see table 3). Although multiple variations are proposed in literature, they all possess great similarities to one another. For instance, innovativeness is sometimes excluded and delivery exchanged with time performance (Neely et al., 1995). According to Neely et al. (1995), time is the fundamental measure of competitiveness and manufacturing performance. Neely et al. (1995) note that several theories and philosophies considering time performance such as just-in-time (JIT), optimised production technology (OPT) with the aim of minimizing throughput time, and throughput accounting which measure profitability in terms of rate of cash flows. Although, time performance is usually considered an aspects of the other dimensions rather than one of its own.

Table 3. Dimension of manufacturing performance. Adapted from Leong et al. (1990),Rudberg (2002), and Beamon (1999).

Dimension	**Subdimension**	**Description**
Cost		Production and distribution of the product at low cost
Quality	Product quality	The manufacture of products with high quality performance
	Process quality	The manufacture of products with high conformance
Delivery	Dependability	Ability meet delivery schedules or promises.
	Speed of delivery	Ability to react quickly to customer orders.
Flexibility	Volume	Ability to react quickly to volume changes of a given product mix.
	Product mix	Ability to react quickly to changes in types of products manufactured.
	Delivery	Ability to move planned delivery dates forward.
	Change-over	Ability of a process to deal with additions to or subtractions from a given product mix.
	Modification	Ability to handle changes in product characteristics.
	Rerouting	Ability to handle machine downtime.
	Material	Ability to meet uncontrolled variations in the composition and dimensions of parts being processed.
	Sequencing	Ability to to deal with uncertainty in delivery times of raw materials.
Innovativeness	Product innovativeness	Ability to quickly introduce new products
	Process innovativeness	Ability to quickly introduce new processes

There are several subdimensions relating to each of the dimensions (Rudberg, 2002, Neely et al., 1995). As with dimensions of MCP there are multiple ways to disaggregate the dimensions into subdimensions. In the following part of section 3.2.2, cost, quality, delivery and flexibility performance will be examined closer. Innovativeness performance has been omitted by the authors due to its lack of relevance in the study.

Cost performance

Due to globalisation, the increased competition has made increasing the productivity in manufacturing plants a constantly growing concern (Jönsson et al., 2008*b*). Optimising the production to achieve cost reductions is imperative to compete with low-wage countries (Jönsson et al., 2008*b*). Resource minimisation is therefore one of the major goals of supply chain analysis (Beamon, 1999). Analysing the cost performance supports more informed operational and strategic decisions regarding performance improvement, value creation, scenario analysis, and effective and efficient resource utilisation (von Beck & Nowak, 2000, Pehrsson, 2013, Jönsson et al., 2008*b*). By letting managers analyse past performance as well as analyse, motivate and influence future performance, the information from cost enables managers "to make judgements about the financial impact of business decisions for future planning and the evaluation of available courses of action" (Pehrsson, 2013, p. 62).

> *"Every action or cessation of action in an organisation consumes economic resources and the understanding of how profits and value are created can be gained through costing"*
> (Pehrsson et al., 2013, p. 1036).

In alignment with the definition of performance measurement by Neely et al. (1995), cost performance is defined as how efficiently and effectively input is transformed to output in the manufacturing function (Pehrsson et al., 2013). Excluding the distribution, the costs associated with a manufacturing system can be divided into:

1) *Manufacturing cost.* Total cost of manufacturing, including labour, maintenance, and re-work costs; and
2) *Inventory cost.* Costs associated with held inventory (Beamon, 1999).

Pehrsson (2013) differentiates manufacturing cost between *prime cost* and *factory expense*. They can in turn be divided into:

1) *Prime cost.* Resource consumption that can be directly tied to specific articles and manufacturing processes:
    i) *Direct labour cost.* Cost of labour directly associated with the manufacturing of goods.
    ii) *Direct material cost.* E.g. cost of raw materials and components.

    iii) *Direct overhead cost.* E.g. machine, factory rent and electricity costs.
2) *Factory expense.* Resource consumption that can not be tied to specific articles and manufacturing processes:
    i) *Indirect labour cost.* E.g. maintenance, administrative, janitorial and factory management labour costs.
    ii) *Indirect material cost.* E.g. consumables, disposable tools.
    iii) *Indirect overhead cost.* E.g. R&D, administrative and office expenses, and selling and distribution expenses (Pehrsson, 2013).

Costs associated with inventory can further be divided into:

1) *Inventory obsolescence.* Costs associated with obsolete inventory, including spoilage.
2) *Work-in-process.* Costs associated with work-in-process inventories.
3) *Incoming stock and raw materials.* Costs associated with inventories at incoming stock level.
4) *Finished goods.* Costs associated with held finished goods inventories.
5) *Backorder/stockout.* Cost associated with shortage of inventory accounting for lost sales/lost production.
6) *Service.* Costs associated with stock management and insurance.
7) *Opportunity cost.* Costs associated with warehousing, capital and storage. (Beamon, 1999, Gunasekaran et al., 2004)

According to Gunasekaran et al. (2004), almost 50% of the current assets consists of inventory in most industries. Together with increasing customer service requirements large uncertainties in production and demand, this results in inventory management having a big impact on costs. Gunasekaran et al. (2004) further claim that inventory costs are often negatively correlated with manufacturing cost; a decrease in inventory cost generally requires shorter lead times and increased flexibility, increasing manufacturing cost (and vice versa). Therefore, they argue that it is important to measure and evaluate inventory costs in relation to manufacturing cost in order to minimise total cost.

Both costing and operational data is needed to support decision-making. While cost performance provides essential information, it is not alone sufficient. A deeper diagnostic insight and a direct connection to the operations is needed to understand what drives performance and causes events (Pehrsson, 2013). Beamon (1999) further warns about the downfalls to relying on measuring cost performance, noting the several issues with traditional cost accounting such as lack of relevance of the cost categories, cost distortion, and inflexibility. Furthermore, she notes that while the manufacturing system operates under minimum cost, it may still demonstrate poor delivery and flexibility performance.

Although the divisions of manufacturing cost into its components and subcomponents can be used as PMs by themselves, Leong et al. (1990) propose a list of more refined PMs:

1) Unit product cost;
   i) Unit labour cost;
   ii) Unit material cost;
2) Total manufacturing overhead cost;
3) Inventory turnover;
   i) Work-in-process;
   ii) Raw material;
   iii) Finished goods;
4) Capital productivity;
5) Materials yield;
6) Direct labour productivity;
7) Indirect labour productivity (p. 115).

Quality performance

Quality performance measurement has since long been established as not only a critical success factor for quality management, but also for attaining competitive advantage (Lockamy III, 1998). Quality performance is commonly divided into two dimensions: product quality and process quality (Netland & Sanchez, 2014, Neely et al., 1995). According to Neely et al. (1995), the adoption of total quality management (TQM) has shifted the quality focus from conformance to specification to customer satisfaction. Although, they note that in light of this, the commonly used concepts of statistical process control (SPC) and Motorola's Six Sigma are primarily tools for measuring process quality.

Process quality can be defined as "the quality of the manufacturing processes" (Netland & Sanchez, 2014, p. 190), traditionally in the terms of conformance to specification (Neely et al., 1995). Typical PMs for process quality in industries have been cost of quality and number of defects (Neely et al., 1995). Regarding, cost of quality, it can be devised into three sub-costs:

1) *Prevention costs.* Expenses in efforts to prevent discrepancies (e.g. costs of quality planning, supplier quality surveys, and training programmes);
2) *Appraisal costs.* Costs expended in the evaluation of product quality and in the detection of discrepancies (e.g. the costs of inspection, test, and calibra-

tion control); and

3) *Failure costs.* Costs expended as a result of discrepancies, and are usually divided into two types:
    i) *Internal failure costs.* Costs resulting from discrepancies found prior to delivery of the product to the customer (e.g. the costs of rework, scrap, and material review); and
    ii) *External failure costs.* Costs resulting from discrepancies found after delivery of the product to the customer (e.g. the costs associated with the processing of customer complaints, customer returns, field services, and warranties) (Neely et al., 1995).

Neely et al. (1995) discuss the concept of "quality is free", declaring that it is based on the assumptions that an increased prevention cost will be more than counterbalanced by the decrease in failure costs in most organisation. They explain that the quality literature motivates this assumption by the existence of an optimal level of quality for a given set organisational conditions. Consequently, the cost of quality is actually the additional cost of the organisation under- or over-performing. However, Neely et al. (1995) note that there is critique against this position, targeting the academic rigour of the cost of quality model as well as the existence of an optimal quality level. They further point out that while many organisation estimate the cost of quality, the essential flaw is that managers fail to act upon reducing it.

Regarding product quality, it can be defined as the manufacture of products with high quality performance (Rudberg, 2002), or the quality of conforming output (Netland & Sanchez, 2014). Product quality is arguably related to many of the eight dimensions of quality proposed by Garvin (1987), i.e.:

1) *Performance.* The products' primary operating characteristics;
2) *Features.* Those characteristics that supplement the products' basic functioning;
3) *Reliability.* The probability of a product malfunctioning or failing within a specified time period;
4) *Durability.* A measure of product life, defined as the amount of use one gets from a product before it breaks down and replacement is preferable to continued repair; and
5) *Aesthetics.* How a product looks, feels, sounds, tastes, or smells. (Garvin, 1987).

Many of these dimensions are intangible and are largely related to customer satisfaction. Their relation to the manufacturing performance is vague as the manufacturing task is arguably to achieve conformance to specification. However, the reliability and durability are nevertheless affected by the manufacturing system performance. Due to the dependency on external feedback and qualitative aspects, the product quality is hard to measure and quantify (Beamon, 1999, Neely et al., 1995)

Netland & Sanchez (2014) claim that good process quality can be be achieved without good product quality, and vice versa. They argue that the first case (i.e. good process quality) would result in an ineffective, but efficient, manufacturing system which generates poor customer satisfaction. The second case (i.e. good product quality), would on the other hand result in an effective, but inefficient, manufacturing system which is distinguished by wasteful processes. However, Neely et al. (1995) note that a good product quality might reduce external failure costs. Nevertheless, it is desirable to have high level of both process quality and product quality (Netland & Sanchez, 2014).

Delivery performance

Delivery performance can be divided into two major sub-dimensions: *delivery reliability*[3] and *speed of delivery* (Neely et al., 1995, Leong et al., 1990). Delivery reliability is defined as meeting the ability to meet delivery schedules or promises, i.e. on-time deliveries (Leong et al., 1990). Speed of delivery is rather straightforward the ability to react quickly to customer orders (Leong et al., 1990), and is as such closely related to lead times.

The delivery performance affects the customer directly, and is the main decisive factor of customer satisfaction (Gunasekaran et al., 2004). Therefore, delivery PMs must not only relate to the organisational goals, but also to the customers' goals and values (Beamon, 1999). Gunasekaran et al. (2004) therefore argues that increasing the delivery performance will increase the competitiveness of the organisation.

Good delivery performance can be achieved by reducing lead time attributes (Gunasekaran et al., 2004). However, the order lead time, and in extension the delivery performance, is affected by lead times both downwards and upwards in the supply chain. However, the scope of this study is only to consider the performance of the manufacturing system, why delivery performance related to e.g. order handling and distribution will be omitted.

Beamon (1999) provides a sample list of quantitative output PMs, of which

[3]Delivery reliability and delivery dependability are used analogously. However, the former is more commonly used in literature.

several are related to delivery performance:

1) *On-time deliveries.* Measures item, order, or product delivery performance:
   i) *Product lateness.* Delivery date minus due date.
   ii) *Average lateness of orders.* Aggregate lateness divided by the number of orders.
   iii) *Average earliness of orders.* Aggregate earliness divided by the number of orders.
   iv) *Percent on-time deliveries.* Percent of orders delivered on or before the due date.
2) *Fill rate.* Proportion of orders filled immediately:
   i) *Target fill rate achievement.* To what extent a target fill rate has been achieved.
   ii) *Average item fill rate.* Aggregate fill rate divided by the number of items.
3) *Backorder/stockout.* Measures item, order, or product availability performance:
   i) *Stockout probability.* Instantaneous probability that a requested item is out of stock.
   ii) *Number of backorders.* Number of items backordered due to stockout.
   iii) *Number of stockouts.* Number of requested items that are out of stock.
   iv) *Average backorder level.* Number of items backordered divided by the number of items.
4) *Customer response time.* Amount of time between an order and its corresponding delivery
5) *Manufacturing lead time.* Total amount of time required to produce a particular item or batch.
6) *Shipping errors.* Number of incorrect shipments made.
7) *Customer complaints.* Number of customer complaints registered. (pp. 283-284)

The PMs listed above do only consider absolute and relative amount of time or quantities. However, they provide an exhaustive of depiction of the dimensions of delivery performance. Gunasekaran & Kobu (2007) remark that there is still a lack of research on how delivery performance best should be quantified; e.g., whether it should be measured as relative percentage or an absolute number. If delivery performance should be measured in the dimensions of time and quantities or in other dimensions such as cost is further debatable. According to Beamon (1999), minimum requirements related to the delivery PMs are often specified by organisations. Although, she notes that the value of overachieving those requirements or failing on them are rarely considered. For instance, what the added value or cost is due to early delivery, or the cost of late delivery, is questions that needs to be answered when evaluting the delivery performance (Beamon, 1999). The importance of these two examples are highlighted by the fact that multiple studies have shown that the speed of delivery is rated secondary to delivery reliability by customers to manufacturing organisations (Gunasekaran et al., 2004, Neely et al., 1995).

Flexibility performance

The need for measuring flexibility performance is especially emphasised by Beamon (1999). As demonstrated in table 3, there are multiple dimensions to flexibility. The manufacturing function is subjected to uncertainties such as product demand, manufacturing complications, new products, and supplier shortages. Flexibility can be considered the ability to handle changes of the circumstances, and is therefore a measure of stress resiliency of a supply chain system (Beamon, 1999). Thus, the ability to adapt to schedule and volume changes in a time and cost effective manner is essential for a successful supply chain management (Beamon, 1999, Gunasekaran & Kobu, 2007).

Measuring flexibility is however hard (Gunasekaran & Kobu, 2007), and the reasons why can be expressed in three main factors:

1) the multiple dimensions of flexibility;
2) flexibility is a measure of potential; and
3) flexibility must be applied to other production objectives, such as volume or delivery (Beamon, 1999).

Item 1) has already been discussed; flexibility is not one aspect, but multiple different ones. This implicates that it is not possible to determine the system flexibility with one measure. However, all aspects of the dimensions listed in table 3 may not be applicable nor important for every supply chain (Beamon, 1999). Regarding item 2); while cost, quality, and delivery are measures of actual operational performance, flexibility is a measure of the potential performance. Even if it has not been demonstrated, the manufacturing system can still possess flexibility (Beamon, 1999). Last, item 3) points out that flexibility is both a qualitative measure and relative to the current system conditions. Beamon (1999) presents four formulas to quantify and compute volume flexibility, delivery flexibility, product mix flexibility, new product flexibility. Next, all four formulas will be presented, exemplifying how flexibility can be measured.

Volume flexibility

The formula for volume flexibility, $F_v \in [0, 1)$, by Beamon (1999), which she describes represent the long-run proportion of demand which can profitably be met by the manufacturing system. Its inherent flaw is the assumption of normal distributed demand, which often underestimates the fat tails of true demand distributions. Using maximum likelihood estimation, F_v can be estimated using other distributions. However, as an indicator for organisations with stable demand, the normal distribution may be adopted successfully as an indicator for volume flexibility.

The formulas are defined as:

$$\hat{\mu_D} = \bar{D} = \frac{\sum_{t=1}^{T} d_t}{T} \tag{3.1}$$

$$\hat{\sigma_D^2} = S_D^2 = \frac{\sum_{t=1}^{T}(d_t - \bar{d})^2}{T-1} \tag{3.2}$$

$$F_v = P\left(\frac{O_{\min} - \bar{D}}{S_D} \leq D \leq \frac{O_{\max} - \bar{D}}{S_D}\right) = \Phi\left(\frac{O_{\max} - \bar{D}}{S_D}\right) - \Phi\left(\frac{O_{\min} - \bar{D}}{S_D}\right), \tag{3.3}$$

where:

- d_t is the demand during period t, and T is the number of periods;
- $D \sim N(\mu_D, \sigma_D^2)$ is the assumed normal distributed demand volume;
- $O_{\min}$ and $O_{\max}$ are the minimum and maximum profitable output volume during any period, respectively;
- $F_v \in [0, 1)$ represents the long-run proportion of demand that can profitably be met by the manufacturing system considered (Beamon, 1999).

Delivery flexibility

The formula for delivery flexibility F_D is by Beamon (1999, p. 288) "expressed as the percentage of slack time by which the delivery time can be reduced" .

The formulas is defined as:

$$F_D = \frac{\sum_{j=1}^{J}(L_j - t^*) - (E_j - t^*)}{\sum_{j=1}^{J}(L_j - t^*)} = \frac{\sum_{j=1}^{J}(L_j - E_j)}{\sum_{j=1}^{J}(L_j - t^*)}, \tag{3.4}$$

where:

- t^* is the current time period;
- L_j is due date period for job j;
- E_j is the earliest time period during which the delivery can be made for job

j;
- $(L_j - t^*)$ is the total slack time for job j in the system;
- $(E_j - t^*)$ is the minimum delivery time for job j in the system (Beamon, 1999).

Product mix flexibility

Beamon (1999) separates between

1) *Product mix flexibility range.* The number of different products that can be produced within a given time period; and
2) *Product mix flexibility response.* The time required to produce a new product mix.

She defines the formula for product mix flexibility range as:

$$F_m = N(t),$$

where $N(t)$ is the number of different product types that can be produced within the time period t, with $t > 0$ and $N(t) \in I^+$ (Beamon, 1999). She defines the formula for product mix flexibility response as:

$$F_m = T_{ij},$$

where T_{ij} is the changeover time required from product mix i to product mix j, with $T_{ij} > 0, \forall\ i \neq j$ (Beamon, 1999).

New product flexibility

New product flexibility is equivalent to the the definition of product innovativeness. Beamon (1999) defines it in terms of the time or cost it takes to introduce a new product to an existing system. Hence, she offers the definitions:

$$F_n = T,$$

where T is the time required to add new products, with T ¿ 0, and:

$$F_n = C,$$

where C is the time required to add new products, with $C > 0$ (Beamon, 1999).

3.2.3 Flow efficiency

Flow efficiency is primarily not a defined performance measure, but rather a principle commonly referred to within Lean. It is put in relation to the more known *resource efficiency*. Although many manufacturing organisations perform well in terms of resource efficiency, they may perform badly in terms of flow efficiency. The result is sub-optimisation, i.e. individual parts of the manufacturing system are efficient but not the system as a whole (Modig & Åhlström, 2012). Figure 8 below shows the separate dimensions of efficiency in this view:

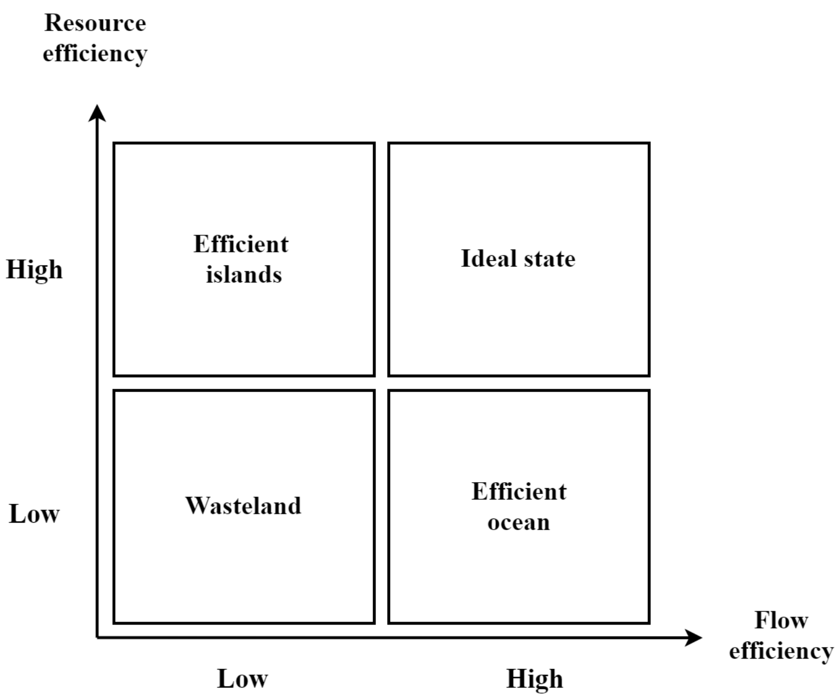

Figure 8. The efficiency matrix. Adapted from Modig & Åhlström (2012)

In figure 8, the ideal state is where both flow- and resource efficiency are high. Focusing solely on resource efficiency, i.e. maximising the utilisation within individual processes, may produce high output but still be wasteful in terms of time (Modig & Åhlström, 2012). In principle, flow efficiency is described in terms of how much of the lead time (or throughput time) in the system that is value-adding. Hence, flow efficiency in percent can essentially be quantified as:

$$Flow\ efficiency\ (\%) = \frac{Lead\ time - Waiting\ time}{Lead\ time} \times 100$$

According to Sundkvist (2014), throughput time in itself can be seen as a flow efficiency measure, as well as *inventory turnover*:

$$Inventory\ turnover = \frac{Total\ income}{Total\ inventory}$$

where the total inventory includes raw material, work-in-process and finished goods inventory. The inventory turnover measures how fast materials are consumed (Sundkvist, 2014).

Sundkvist (2014) further argues that the difference between resource efficiency and flow efficiency can be described in terms of *throughput time* (or lead time) and *throughput rate*. That is, the former describes the total time it takes for a product to be processed in the system and is thus an absolute measure of the flow efficiency. The latter describes how many products that can be produced per time unit, and is rather a measure of resource efficiency. The trade-off between the two is that increasing the throughput rate typically increases the throughput time, through increased WIP. This is closely related to managing bottlenecks, as reducing the WIP may cause bottleneck processes to ”starve” occasionally, and thus reduce the whole throughput of the system.

3.2.4 The individual performance measure

The building blocks of a PMS are the individual PMs. To develop a PMS that fulfils the four characteristics of an effective PMS presented by Beamon (1999), the characteristics of an effective PM must first be established. This will be covered in the first part of this section 3.2.4. Due to the more or less infinite number of PMs, to facilitate a structural approach in developing a PMS that achieves inclusiveness and consistency, there is a need of categorising PMs. This will be covered in the second part of the section.

Parker (2000) notes that there is scepticism in organisations towards PMs, due to the difficulties of measuring the right aspects, comparing like-to-like, and comparing through time. According to Neely et al. (1995), PMs can be evaluated through the following questions:

1) What are they used for?
2) How much do they cost?
3) What benefit do they provide?

The following part of this section 3.2.4 will examine the characteristics of PMs and how they can be categorised.

Characteristics of manufacturing performance measures

Following the relation between manufacturing performance areas described in section 3.2.1, PMs in manufacturing should be chosen with respect to the manufacturing strategy (Beamon, 1999, Parker, 2000, Neely et al., 1995, Melnyk et al., 2004). Beamon (1999) points out two reasons why this is important; first, it enables management to determine if strategy goals are met, and second, PMs dictates the focus of the organisation and can therefore be irrelevant or even counterproductive to the strategic goals. Regarding the second argument, Parker (2000) adds that PMs must lead to improvement by encouraging action or behavioural change. To facilitate this, it is important that PMs are combined with goals that are realistic and achievable (Parker, 2000). Comparison with other simulated scenarios or historical outcomes do indeed give an insight of the relative performance, however, assessing the objective performance must be done with respect to goals assigned to each metric or measure.

Another imperative characteristic of PMs that has been highlighted is that they are understandable (Gunasekaran et al., 2004, Parker, 2000, Neely et al., 1995). If the users can not understand the PMS, they will not be effectively applied or neglected.

Categorising Performance Measures

On the top level, performance measures can be divided into qualitative and quantitative PMs. However, Gunasekaran & Kobu (2007) argue that there is a need for more quantitative PMs and that that qualitative PMs should be translated into quantitative. Beamon (1999) agrees with this position and notes that "[w]hen analyzing system performance, qualitative evaluations such as 'good', 'fair', 'adequate', and 'poor' are vague and difficult to utilise in any meaningful way. As a result, quantitative performance measures are often preferred to such qualitative evaluations" (p. 275). Gunasekaran & Kobu (2007) further note that quantities and qualitative PMs are heavily interdependent, and that understanding their complex causal relationships between them is essential.

Financial and non-financial performance measures

A further top level breakdown of PMs is the nature of the resource measured, i.e. between financial and non-financial PMs. Historically, performance measuring has more less only been solely focused on financial PMs, closely related to cost accounting (Gunasekaran et al., 2004, Gunasekaran & Kobu, 2007, Neely et al., 1995, Beamon, 1999, Parker, 2000). Since the 90s, there has been substantial critique against the use of financial PMs in performance measurement. The general arguments against financial PMs are that:

1) they tend to be very insular or inward-looking;
2) they fail to include the less tangible aspects;
3) they are lagging indicators (Parker, 2000).

Especially, the critique has been aimed at the excessive use of and reliance on financial PMs.However, there is a consensus among the research community that financial PMs are indeed necessary. Gunasekaran et al. (2004) argue that it is important to balance PMs, as financial PMs are important for strategic decisions and external reporting, while non-financial PMs are better suited for day-to-day control of operations. This stance of balancing operational and financial PMs is furthermore strongly emphasised in the *balanced scorecard* performance management tool proposed by Kaplan & Norton (1992).

In addition to the crude top-level categorisations of PMs described above, there has been much research on more detailed categorisation frameworks. Many of these frameworks have vast differences between them, taking on different perspectives on PMs. In the remainder of this section, the categorisations proposed by Gunasekaran et al. (2004) and Melnyk et al. (2004) will be discussed. Other notable mentions include the categorisation by Parker (2000) who distinguishes between outcome, action, input and diagnostic PMs, and Beamon (1999) who distinguishes between resources, outcome and flexibility PMs.

Categorisation based on decision level and resource nature

Gunasekaran et al. (2004) propose a framework for performance measures categorise financial and non-financial PMs into their influence on decision-making in different levels of management in the organisation. Gunasekaran et al. (2004) assign the PMs into strategic, tactical, and operational level metrics, arguing that this leads to a more appropriate performance measurement and fair decisions.

Gunasekaran et al. (2004) defines the PMs corresponding to the different decision levels accordingly:

1) *Strategic.* Influence the top level management decisions, very often reflecting investigation of broad based policies, corporate financial plans, competitiveness and level of adherence to organisational goals.
2) *Tactical.* Deal with resource allocation and measuring performance against

targets to be met in order to achieve results specified at the strategic level. Measurement of performance at this level provides valuable feedback on mid-level management decisions.

3) *Operational.* Require accurate data and assess the results of decisions of low level managers. Supervisors and workers are to set operational objectives that, if met, will lead to the achievement of tactical objectives.(p. 335)

In table 4, these decision level categories are put into the context of nature of the resource measured, i.e. financial or non-financial.

Table 4. Categorisation of PMs. Based on Gunasekaran et al. (2004)

Type	**Description/Examples**	
	Financial	*Non-financial*
Strategic	Net profit vs. productivity ratio, variations against budget	Order lead time
Tactical	Supplier cost saving initiatives, delivery reliability	Effectiveness of master production schedule
Operational	Total inventory, manufacturing cost	Capacity utilisation

Gunasekaran & Kobu (2007) argue that this categorisation leads to better understanding regarding which PMs should be applied at different levels of the organisation. They further claim that this categorisation will align strategies at different decision levels so that right decisions can be made, supporting the achievement of overall goals and objectives of the organisation.

Categorisation based on tense and resource nature

When categorising PMs, Melnyk et al. (2004) base it on what they argue are two primary attributes of PMs: *focus* and *tense*. Focus describes the nature of the resource observed by the PM, being either financial or operational (or non-financial). Tense describes the intention of the PM, i.e. whether it is judging performance outcomes or predicting future outcomes. Based on these attributes, the PMs can be sorted in a matrix, which can be seen with examples of PMs in figure 5.

The use of predictive PMs is fairly new (Melnyk et al., 2004), as PMs historically has been used only "to monitor past performance and stimulate future action" (Neely et al., 1995, p. 109). However, there is an increasing demand on finding

Table 5. Categorisation of PMs. Based on Melnyk et al. (2004).

Type	Description/Examples	
	Financial	*Non-financial*
Outcome	Return on Asset	Elapsed lead time
Predictive	Overtime cost (predictive for budget overruns	# process steps and overruns (predictive for lead times)

predictive PMs which allows managers to observe trends so that action can be taken preventivly before events occur (Neely et al., 1995). Regarding predictive and outcome PMs, the emphasis on *use* is important as a predictive PM in one context can be an outcome PM in another. While an outcome use of a PM implies making inferences on the future performance by studying the past, a predictive use focuses on preventing problems from occurring by analysing processes that will impact an outcome (Melnyk et al., 2004). Therefore, the combination of outcome and predictive use of PMs can effectively be applied by using an aggregated PM as outcome and one or more of its constituents as predictive.

3.2.5 The performance measurement system

The three key functions of a PMS are control, communication and improvement (Melnyk et al., 2004). A PMS should allow managers to evaluate and control the performance of the production system, communicate the result and impact to the stakeholders, and locate areas of improvement. In order to fully assess the performance of the manufacturing system and reconfiguration effects, the PMS needs to offer a complete and accurate representation. In the study by Beamon (1999), a framework for the selection of performance metrics for manufacturing supply chains is developed. She defines four characteristics of an effective PMS (see table 6).

Table 6. Characteristics of an effective performance measurement system. Based on Beamon (1999).

Property	Description
Inclusiveness	Measures all pertinent aspects.
Universality	Allows for comparison under various operating conditions.
Measurability	The data required are measurable.
Consistency	Measures consistent with organisation goals

The hierarchical categorisation of PMs proposed by Gunasekaran et al. (2004), with strategic being the highest level, followed by tactical and operational at the bottom level, requires integration of PMs. In order to avoid sub-optimisation, the PMs at lower level must aggregate into the higher level, in accordance with the performance pyramid in figure 7 and consistency characteristic in table 6.

Number of metrics

Using a single measure for an attribute is attractive due to its simplicity. However, Beamon (1999) points out that they hardly fulfil the characteristics of an effective performance measurement system, most of them failing to be inclusive. On the other side of the spectrum, all activities cannot be measured; PMs needs to be selective and focus on activities which are most important with respect to the strategic goals (Parker, 2000). To better assess the performance, the PMS should only include a few key PMs. While being inclusive, the PMs of a PMS should be the ones that capture the essence of the manufacturing performance. Beamon (1999) notes that picking a single PM to be representative of a strategic goal might be difficult in practise.

The performance measurement system environment

It is important to understand that the PMS is not only a set of measures but a management strategy and methodology in itself. As such, the PMS will interact with its environment; both the internal environment (the organisation itself) and the external environment (the market in which the organisation operates) (Neely et al., 1995). Regarding the internal environment, as organisations operates with internal goals and incentives, it will always affect how the PMS is perceived and used. This is often an issue with functional structure organisations, where different evaluation and reward systems leads to conflicts between functions, e.g. manufacturing and marketing (Neely et al., 1995). Neely et al. (1995) further note that the PMS must not only be consistent with the strategy but also the culture of the organisation. They exemplify with an organisation with a culture of blame which introduces a PM which measures defects per operator. It would result in the operators lying, leading to the PM representing false data with potentially critical impact on the decisions and actions the organisation pursuits.

The external environment can be divided between customers and competitors, and there is a necessity that the organisation-wide PMS reflects these elements (Neely et al., 1995). The former refers to properly considering customer satisfaction in terms of quality and delivery. The latter element, i.e. competitors, largely revolves around the ability to benchmark, i.e. "[to] search for industry best practices that lead to superior performance" (Neely et al., 1995, p. 106).

3.2.6 Conclusions

Performance measurement is a key activity in organisations which quantifies action into efficiency and effectiveness. By refining and distilling data, and providing data-based decision support, performance measurement provides an understanding of the processes and activities in the manufacturing organisation, therefore enabling both the identification of problems but also of success.

Manufacturing performance can be observed from two perspectives: The first one is the manufacturing competitive priorities; cost, quality, delivery, flexibility, and innovativeness performance. These priorities constitute the key performance dimensions on which manufacturing organisation can compete. The other perspective is the performance pyramid which describes the hierarchical structure of manufacturing performance. Starting from the crude operational performance dimensions, they get aggregated upwards into higher level performance dimensions, eventually leading to the realisation of the corporate vision.

A performance measure should be chosen by weighing its benefits to its cost. However, it is imperative that the performance measure is aligned with business/manufacturing strategy and fully understood by its users. Performance measures can further be categorised in several stages. First, between quantitative and qualitative, of which the latter is universally preferred. Second, performance measures can be separated by whether they are financial or non-financial, of which the former have been heavily criticised for their dominance. Together, the individual performance measures are composite parts of the whole performance measurement system (PMS). The PMS should be designed from a holistic perspective, taking into account the environment in which it is used, both internally and externally. Furthermore, it should uphold the characteristics of inclusiveness, universality, measurability, and consistency.

3.3 Simulation

Ören (2009) finds that the concept of simulation has proven to be of great use as decision support in a variety of different fields and already in the 1970s some 120 areas of application could be distinguished in science and industry. In particular, Discrete Event Simulation (DES) as a tool for designing, analysing and improving manufacturing systems is an extensively applied concept in research and industry (see for example Negabahn & Smith, 2014).

The following section presents a theoretical foundation for the concept of simulation. The focus is particularly on the applications of discrete-event simulation (DES) in manufacturing systems as a decision support tool and for optimising or improving the system performance.

3.3.1 Discrete-event simulation

A discrete-event simulation model is one which models a system of entities (dynamic or static), resources, activities, delays and attributed at the basis of time-driven events causing changes in the system's state variables. An event can be defined as an occurrence which causes a change in the state of the system (Banks, 1998).

3.3.2 Discrete-event simulation as decision support

Although the wide range of applications for DES in manufacturing has continued to grow, AlDurgham & Barghash (2008) argue that it should on a general level primarily be seen as a decision support tool. Such simulation-based decision support can be applied in several different ways as listen in table 7

Table 7. Types of Uses of Simulation for Decision Support. Adapted from Ören (2009).

1.	*Prediction* of behaviour or performance of the system of interest within the constraints inherent in the simulation model (e.g. its "granularity")
2.	*Evaluation of alternative* models, parameters, experimental and/or operating conditions on model behaviour or performance
3.	*Sensitivity analysis*
4.	*Engineering design*
5.	*Virtual prototyping*
6.	*Planning*
7.	*Acquisition* (or simulation-based acquisition)
8.	*Proof of concept*

Why simulation can be used effectively for decision support can be summarised to four main reasons:

1) A simulation facilitates the understanding of the real system and its behaviour.

2) The actual exercise of building a simulation model reveals previously hidden relationships and provides a systematic way to analyse the situation.
3) A simulation model can facilitate communication and provide a basis for discussion.
4) "What-if" analyses can be carried out, allowing the decision-maker to test the effects of different alternative scenarios without having to make changes to the real system. (Semini et al., 2009)

Decision support systems (DSS)

Simulation implemented as a tool for continuous use for scenario testing, "what-if" analysis and alike, can be described as a form of Decision Support System (DSS). Tolk et al. (2009, p. 404) defines Decision Support Systems as: "[..] information systems supporting operational (business and organizational) decision-making activities of a human decision maker." When simulation is a feature in such a system, Tolk et al. (2009, p. 405) separately define Decision Support Simulation Systems (DSSS) as "simulation systems supporting operational (business and organizational) decision-making activities of a human decision maker by means of modelling and simulation."

3.3.3 Issues and limitations in simulation models

A simulation model can be seen as the computerised implementation of a conceptual model, which inevitably is a simplification of the real system. Some sources of simplifications and assumptions in the model are related to uncertainties about the phenomena and processes modelled (Reynolds Jr., 2009). An example could be a sub-process which is assumed to be deterministic when it in fact is stochastic. Vice versa, some processes could in reality be deterministic but their dynamics so complex and hard to evaluate that they are modelled as stochastic (referred to as *aleatory uncertainty*). There can also be a degree of so-called *epistemic uncertainty*, meaning that the stochastic behaviour that is simulated not accurately represents the real dynamics of the process' behaviour (Reynolds Jr., 2009). Such issues could occur when for example the processing time in a machine is assumed to be random with some probability distribution, but it is difficult to obtain a large enough amount of data on its behaviour to find a reasonably accurate distribution, or such a distribution is simply not known.

Even if the above mentioned uncertainties are handled, a central question remains regarding the level of detail included in this model. i.e. its level of *abstrac-*

tion, and what level of complexity the simulation model should have in order to accurately enough represent the real system. Robinsson (2015) argues that an increasing level of complexity (and scope) of the conceptual model pays off in model accuracy to a certain extent, but never reaches 100 %.

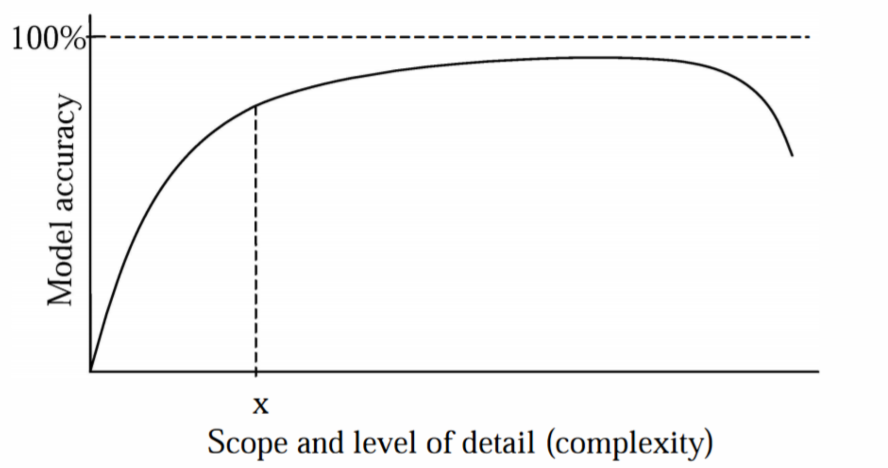

Figure 9. How simulation model accuracy changes with the complexity of the model. (Robinsson, 2015).

Figure 9 shows that the model will never be completely accurate, no matter the attempts to capture every detail in the real system. It also shows that increasing its complexity not only has diminishing returns in terms of model accuracy, at some point the accuracy will even start to decrease. A suitable level of complexity is represented with the point x, a point where an increase in complexity requires great effort but barely increases the accuracy of the model. This point, however, can be difficult to find (Robinsson, 2015).

In general, the above mentioned modelling issues need to be handled in the process of verifying and validating the simulation model. A verified simulation model is one that correctly represents the conceptual model of the system. A validated simulation model is one that reasonably well represents the real system (Banks, 1998).

3.3.4 Manufacturing applications

AlDurgham & Barghash (2008) propose a comprehensive and generalised framework for organising the areas of simulation application in manufacturing in a systematic way.

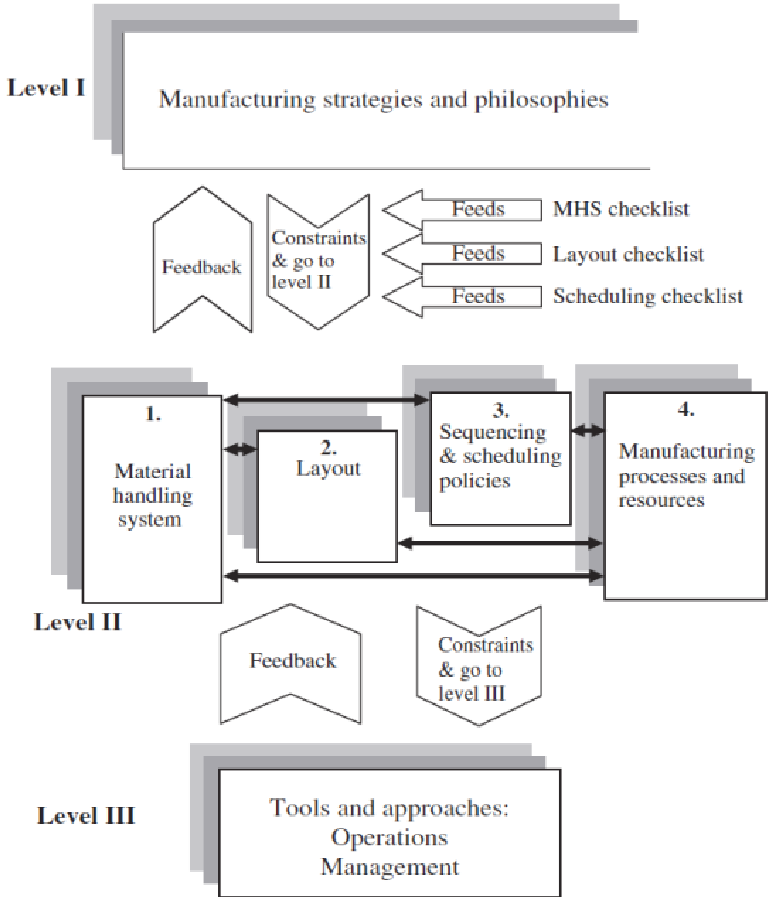

Figure 10. Simulation Application Framework for Manufacturing (Macro view). (AlDurgham & Barghash, 2008).

The framework in figure 10 shows that the application of simulation is connected to different levels of the manufacturing organisation. Level I is the basis for a simulation project or study, the domain in which there is a certain purpose of applying simulation. Common examples could be in Lean or JIT projects as a means of identifying wastes, optimising parameters or testing, designing, improving or analysing the manufacturing system. Level II entails the common areas of simulation application, or decision domains; Materials handling, Layout, Scheduling and Manufacturing processes and resources. These are the actual activities, policies, processes and resources which are studied with simulation, with respect to the manufacturing strategies and objectives set out. More specifically, the previous level has put certain constraints and requirements on the Level II area which is studied in the simulation, specified in "Checklists" aiming at translating the Level I domain into actual conditions. Level II applications of simulation can generally be divided into three main purpose categories:

1) design a system from scratch,
2) improve system on hand,
3) modify/change system on hand (Re-engineering),

where 1) and 3) typically would be followed by 2) in the form of continuous improvement. Level II applications put in turn constraints on the lowest level, Level III, the case in which simulation is applied to support operational routine decisions regarding the system on hand. Level I and II typically represent projects in which simulation is a tool for achieving the goals and conditions specified in Level I, within one or several decision domains and purpose categories in Level II. An important observation from Level II is that the decision domains are interrelated and usually cannot be studied independently in a simulation.

3.3.5 Theory of Constraints, the *Japanese lake* and bottleneck detection

Specific applications of DES have been developed, which focus on identifying and improving bottlenecks in manufacturing systems. Pehrsson et al. (2016) proposes a method using simulation-based multi-objective optimisation for doing so, which can be incorporated into the general improvement method Theory of Constraints (TOC). TOC is based on an iterative effort of identifying and removing constraints in the system, in order to improve overall throughput. Pehrsson et al. (2016) uses the method of Simulation-based Constraint Identification (SCI) to simplify and facilitate the identification step in TOC for complicated systems with moving bottlenecks. He shows that DES used in combination with other techniques has shown itself useful to combine with the application of TOC through ranking the most commonly occurring constraints in the manufacturing system, allowing the decision-maker to prioritise the most prominent one.

This principle of finding constraining factors in the system has similarities with Japanese production philosophies, such as the one commonly referred to as the *Japanese lake*. According to Farahani (2011) the idea often revolves around reducing inventory, seen as the water in a lake. With too much water (inventory), the actual issues and root causes of poor performance, such as bottlenecks, are hidden.

While lowering the water level in the Japanese lake would reveal bottlenecks, it might be difficult and risky to do so in a real system without knowing the effects on beforehand. To instead apply a methodology as Pehrsson et al. (2016) demonstrates, and "experiment" within a virtual model, the methodology of finding and removing constraints would not only be more effective (through ranking the most prominent ones). Finding the bottlenecks would be done virtually, without risking to deteriorate the performance of the real system in the process.

3.3.6 Cost modelling

Including cost modelling is required to properly analyse the cost performance of the manufacturing system. DES has for a long time been used together with cost models to efficiently cost parts and products, and represents one of the key application areas for manufacturing simulations (Krishnamurthi et al., 1997).

Modelling the factory expense is generally intricate and might even be considered unnecessary when optimising the manufacturing system (Jönsson et al., 2008*a*). While prime costs such as direct material is quite straightforward to model as the resources are tied to specific articles and activities, there still needs to be estimations on how the other manufacturing costs affect the part or product unit cost. Direct overhead costs, and sometimes even direct labour, needs to be allocated correctly. Depending on how these costs are allocated, the modelled cost performance can differ greatly.

Costing has been researched for a long time, and is still a highly debated area(Pehrsson, 2013, Sundkvist, 2014). Historically, when labour was a major part of the manufacturing cost, overhead cost were allocated based on labour hours using total absorbation costing (Gunasekaran & Kobu, 2007). Productivity today depends on capital productivity, which implies that the overhead should rather be allocated based on machine hours (Gunasekaran & Kobu, 2007). However, the most commonly used approach in modern simulation applications is activity based costing (ABC) (Gunasekaran & Kobu, 2007, Jönsson et al., 2008*a*, Pehrsson, 2013). The ABC has however sustained heavy criticism due to the complicity of managing and updating the data required. Kaplan & Anderson (2007) responded to this criticism by proposing a new way of allocating cost named time-driven ABC (TDABC). Opposite to the crude ABC, TDABC considers unused capacity (Kaplan & Anderson, 2007). TDABC consists of two steps:

1) Calculating capacity cost rate [cost/resource capacity unit], by;
    i) calculating the cost of all resources supplied to a process for a given time period [total cost]; and
    ii) dividing this total cost by the resource capacity available during the time period [total resource capacity].
2) Estimating the demand for resource capacity that each cost object requires [resource capacity unit] (Kaplan & Anderson, 2007).

While the theory allows for resource capacity to be universal, the main approach suggested by Kaplan & Anderson (2007) is using time. Hence, TDABC requires first an analysis of the cost of the supplied resource to a process and the time it is available, and secondly the time consumed in the process by the cost object (Sundkvist, 2014).

A general principle is that cost models should be able to produce good estimations of cost using as small amount of information as possible (Pehrsson, 2013). Therefore, there exist multiple specialised cost models depending on the application such as for different production process and system design production costing (Jönsson et al., 2008*a*). One can further differentiate between microeconomic and macroeconomic models for estimating manufacturing cost; the former deal with costing based on how specific process parameters affect the part cost, whilst the latter are more aggregated and deal with how cycle time, rather than the processes affecting the cycle time, affect the part cost (Jönsson et al., 2008*a*).

Due to the many benefits of using cost modelling together with simulation (Pehrsson, 2013, Krishnamurthi et al., 1997), several cost models have been proposed with different approaches.(Jönsson et al., 2008*a*) presents an extensive and detailed macroeconomic cost model, which describes how costs is added in every process to the part cost. The model is intended to be used as a support tool in combination with a simulation model to analyse the effect of different scenarios on the part cost (Jönsson et al., 2008*a*). The model costs the part using a ABC-related allocation, however only focusing on manufacturing costs. The model requires over 30 parameters, and the researches themselves note that the requirement of accurate inputs is the main pitfall of the model. They identify parameters such as relative loss in production rate, downtime rate, scrap rate and setup time to be the most important while noting that estimating equipment costs is perhaps the greatest challenge.

Other notable mentions is the model suggested by (Pehrsson, 2013), which is an incremental aggregated cost model to be used with simulation-based multi-objective optimisation for computing the running cost of manufacturing system. A major application of his model is evaluating the impact of investments. Sundkvist (2014) on the other hand applies TDABC in a framework to analyse how cash flows are affected by improvements, by investigating the relationship between the changes in inventory book values and productivity improvements.

No model is however perfect and Beamon (1999) stresses that there are several pitfalls when modelling costs. Among others, she mentions typical failing factors as lack of relevance of cost categories, cost distortions due to inadequate allocation of overheads, and incorrect assessment of inventory costs. Beamon (1999) further highlights that cost modelling can easily be insular by exemplifying the importance of considering the part/material size when modelling inventory cost: A low cost item may due to its large size occupy much space, and thus effectively be expensive (Beamon, 1999).

3.3.7 Conclusions

Three main observations from the literature on simulation as a decision support tool are:

1) application of simulation starts in Level I, i.e. first setting long-term manufacturing goals and then using simulation to design, analyse, improve or operate the system in order to reach them;
2) simulation itself can only evaluate alternatives. Such evaluations are made based on a defined set of performance metrics;
3) as with testing improvement alternatives virtually before implementing, simulation can also be used effectively to detect and analyse bottlenecks e.g. in the process of applying TOC
4) cost modelling in simulation is intricate and typically requires large amounts of accurate and updated input data
5) a general principle in cost modelling is being able to produce as accurate estimations as possible, with the smallest possible amount of input data;

A simulation model can be described as a function representing a specific system, which maps a defined set of input parameter values (albeit often stochastic) to a set of output measures (often also stochastically represented). The specified values of the input parameters could be described as a ”scenario” to be evaluated and the quantitative evaluation of such a scenario is the output measures. In order to be able to meaningfully compare different scenarios, the set of output measures needs to be carefully defined, as AlDurgham & Barghash (2008) point out. For example, as Kádár et al. (2004) note, when comparing different simulated production schedules it is likely that their performance cannot be unequivocally determined. Instead, depending on the measured criteria by which the schedules are evaluated one might get ambiguous results.

3.4 Theoretical framework

This section covers the development of a theoretical framework, i.e. the Simulation Application Performance Evaluation Canvas (SAPEC). The framework is based on a synthesis of the three topics covered in chapter 3, namely; decision-making in manufacturing, DES as decision-support, and performance evaluation.

3.4.1 Simulation Application Performance Evaluation Canvas (SAPEC)

The intersections shown in figure 2 can be synthesised and conceptualised in several different ways. In general, section 3.1 deals with how decisions can be categorised based on the organisational levels on which they typically are made, on which areas they concern and on their characteristics. It also notes that the decisions made can be described as setting values for decision variables in the different decision areas, based on the competitive priorities set in the manufacturing strategy. Section 3.3 is concerned with the applications of DES, particularly in the context of decision support. The applications can be defined as both the purpose or type of use of simulation, and the area within the manufacturing system where it is applied. Section 3.2 outlines which types of performance measures to apply in different contexts, their respective properties and in what way they should be applied.

Figure 11 below is a theoretical framework developed by the authors, the Simulation Application Evaluation Canvas (SAPEC). The SAPEC links the decision-making domains, performance measure types and DES application areas in order to create a clearer picture of what leads to a certain set of metrics in the context of applying DES as decision support. The model itself leaves to the user to specify exactly which measures to use; instead it functions as a facilitator and point of reference in which to map out the intended application of simulation in manufacturing and the stakeholders/decision-makers involved.

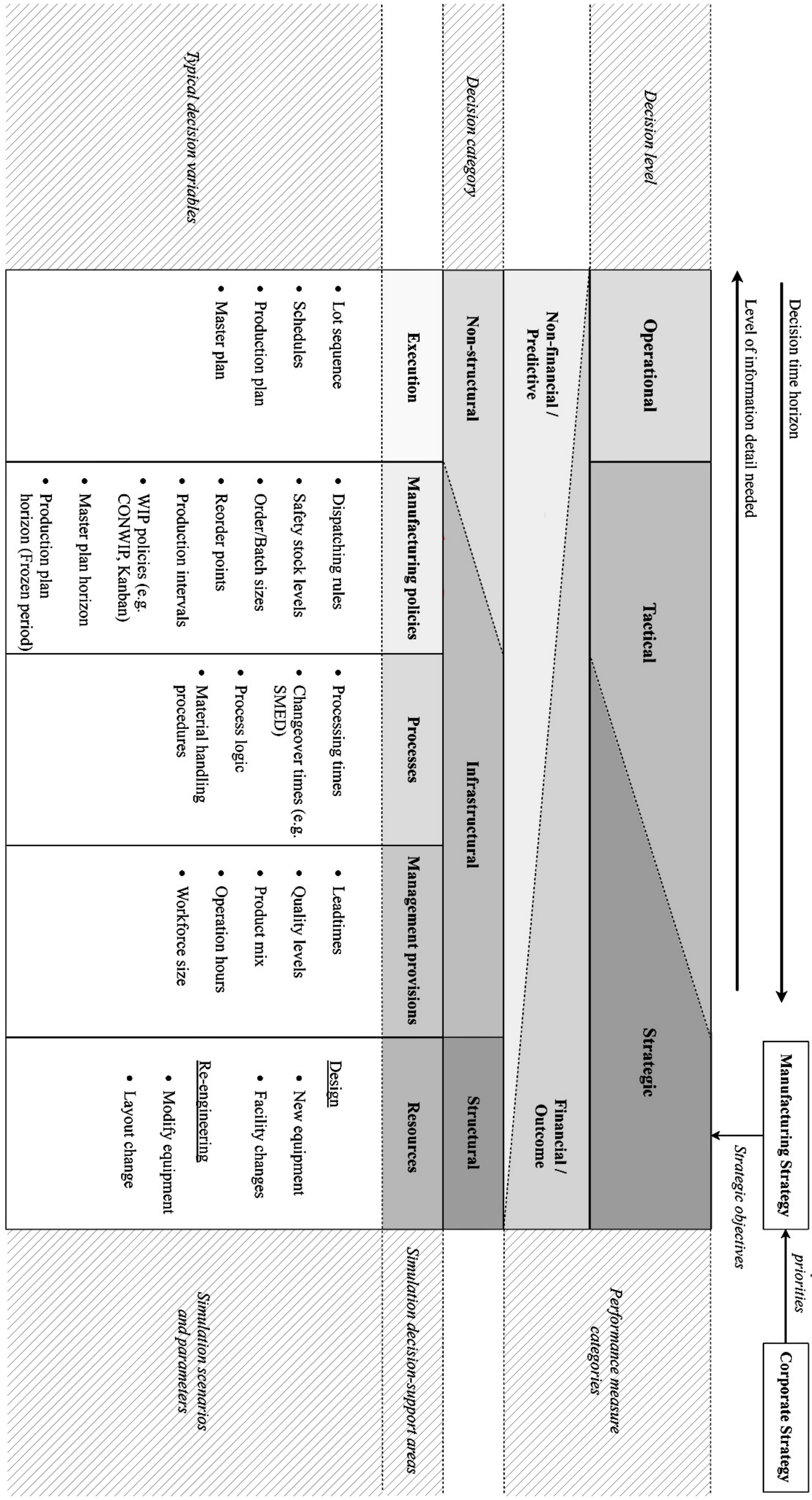

Figure 11. Simulation Application Performance Evaluation Canvas (SAPEC). (Source: Authors' own work).

The starting point in figure 11 is the corporate strategy, which forms a set of competitive priorities. These are a crucial part in forming the manufacturing strategy, which can be translated into a set of objectives (e.g. reducing costs, improving quality, increasing flexibility or increasing productivity) (see section 3.2.2). The strategic objectives are primarily a concern at the **Strategic** *decision level*, but are translated into more specific, shorter-term objectives at the other decision levels; **Tactical** and **Operational**. Also, as the arrows at the top illustrate, the time-horizon of a decision is typically longer for Strategic decisions than for Tactical and Operational, whereas the level of detail in, and volume of, information needed to support the decision is lower. Note also that the decision levels correspond their own respective category of relevant performance measures. The performance measures can however also be divided into financial/non-financial measures or predictive/outcome measures. These categories can typically and in principle be organised in parallel with the decision levels as shown in the figure, although without a clear separator of when to use one or the other. The *decision category* is also relevant in the sense that it typically corresponds to which type of decision that is made. **Structural** decisions are defined as long-term and concern larger investments, typically in physical entities such as new machinery or facilities whereas **Infrastructural** decisions are more related to how to operate and utilise the existing resources (Wheelwright, 1984).

In the defined decision- and performance measurement structure, some relevant DES decision-support areas can be mapped out.

Resources

This application area refers to Strategic and Structural decisions, such as designing new, or modifying, equipments or facilities. This area is characterised by a longer decision horizon, high capital investments and defined as a level of decision-making typically managed on outcome- and financially oriented measures. Simulation can aid both in designing new "greenfield" systems, or in modifying existing systems. "What is the system supposed to consist of?"

Management provisions

Management provisions concern high-level decision variables and simulation scenarios that are related to the infrastructure of the manufacturing system; i.e. fundamental principles, conditions and constraints that the manufacturing system operates under. Examples can be which products to produce, the size of the workforce or the acceptable quality levels. Setting the Management provisions could have a shorter decision horizon than investing in resources, and thus falls under Strategic/Tactical decisions. It could therefore be based on a combination of Financial/Outcome- and Non-financial/Predictive measures. "What can and should the system do?"

Processes

The processes within the manufacturing system could be of both Strategic and Tactical concern, and involve both minor modifications or major projects within Business Process Re-engineering (BPR). Some decision variables or simulation parameters/scenarios are the processing time in machines, material flows or whether to conduct Single-Minute Exchange of Dies (SMED). These type of decisions are also typically based on a combination of Financial/Outcome- and Non-financial/Predictive measures. "How should we use the resources?"

Manufacturing policies

This DES decision support area is a common domain to apply simulation and involves more detailed principles around how to carry out the processes and activities in the system. Decision variables and parameters to simulate could be what dispatching rules to use, re-order points in inventories, safety stock levels, the production frequency etc. These decision are typically made on a tactical level and are not very difficult to change over a reasonably long time, and do not necessarily concern the actual infrastructure of the system. Although their financial implications and outcomes can vary in size, they are typically based primarily on non-financial or predictive performance measures. "What should be the guidelines for operating the system?"

Execution

This application area concerns the lowest decision level and neither the structure or the infrastructure of the system, rather the actual operation of it. A single decision does not apply for very long, as in the case of setting a production plan for a number of weeks ahead or weekly planning on which batches or orders to run on which machines, at which times. The performance on this level of the system is typically difficult to represent in any relevant financial terms and are more focused on the flow and workload on the factory floor. "What should the resources and workforce do in the near future?"

A general principle of the framework in figure 11 to emphasise is that the choice of performance measures to apply in a certain application of simulation is affected by several aspects. Firstly, the manufacturing strategy is what sets the objectives and therefore determines what is actually relevant to measure at all, what measures to improve on or what impacts to investigate in a "what-if" scenario. Secondly, the decision levels and categories concerned with the scenario simulated may require different types of information to make a decision. Thirdly, as discussed in section 3.2.5, an important feature of a good PMS is that the measures used on lower levels are related and aligned with the ones used on higher levels.

Furthermore, what measures that are relevant in a certain simulation application may also be affected by whether the purpose of the simulation is to improve/optimise the performance of the system, or if it is conducted as a "what-if" simulation to investigate and highlight impacts of a specific scenario. In order to improve the performance, there needs to be some defined measure(s) to improve on.

The SAPEC categorises various decision variables and simulation parameters/scenarios into the five main application areas listed above, but they are not necessarily studied in isolation. As AlDurgham & Barghash (2008) conclude, many simulation applications in Manufacturing are interrelated. Changing one parameter in one application area may well affect the performance in others and an improvement project involving simulation is likely to study several of them. A what-if analysis using simulation may also be concerned with studying the impacts in more than one or a few specific parts of the manufacturing system. Furthermore, if a strategic objective is to for example reduce lead times, and simulation is applied within a management initiative to achieve that, there could be several different areas to study. There could also be several different parameters to change, which all contribute to improving on the primary performance measure.

Finally, an important logic in the SAPEC is that higher-level applications in the right part of the framework will in many cases need to include lower-level measures. This is based on, and in line with, the Performance Pyramid in figure 7. For high-level decisions, the most relevant performance measures are aggregated out of the ones on the lower decision-levels. But it does not necessarily have to mean excluding their components from the decision-support. If designing a new factory or layout, aggregated financial measures alone may not provide all the information needed to evaluate whether a design choice is appropriate or not.

Chapter 4

External view

This chapter presents the data collected from four unstructured interviews. The interviewees were purposively sampled with the criterion of having either theoretical or practical experience of developing, implementing and/or evaluating production simulations. The interviewees, i.e. Videsson (2017), Wiklund (2017), Pehrsson (2017) and Marklund (2017), are described in more detail in table A2 in appendix A.

4.1 Decision making

Pehrsson (2017) affirmed that support for strategic decisions differ from that for operational decisions. For operational decisions, the objective is the short-term removal of constraints and the management of current production challenges, he noted. Regarding operational investment decisions, they are subsequently focused on improving the system with the minimum resources. Rather than making an assessment between multiple objectives, he argued that it is better to focus on removing constraints in the production when making operational decisions.

At the long-term strategic decision level, Pehrsson (2017) noted that multiple factors needs to be taken into consideration. These include both external effects such as world economy changes and technology advancements, as well as preparation for future decisions in the production system. Compared to operational investment decisions, he considered it important to focus on more than running cost, cost of investment and productivity; scalability, reconfigurability and agility are also important factors to consider.

Videsson (2017), Marklund (2017) and Pehrsson (2017) agreed that information for decision support should generally be more detailed on operational level decisions and become increasingly aggregated toward strategic level decisions. Marklund (2017) further emphasised that the information needed for decision support must be clearly defined with respect to the purpose of doing the simulation. Otherwise, he claimed, you will end up with with too much irrelevant information, causing information overload. However, Marklund (2017) speculated that a larger volume of information might be relevant if there exists a key individual at the organisation with deep knowledge of the operations. This individual may gain a holistic understanding of the interrelations in the dynamics which he/she can communicate in a condensed form to decision makers and relevant stakeholders.

4.2 Performance measure properties

In this section, the interviewees' perspectives on different properties of PMs are described. This includes the level of aggregation of PMs, the use of relative PMs, the predictiveness of lagging PMs in a simulation, and the automated generation of PMs.

4.2.1 Aggregation

Pehrsson (2017) was critical of using aggregated PMs such as OEE or running cost when comparing simulated actions, stating that it is better to use crude PMs which are relatively easy to interpret. He emphasised that understanding and analysing the impact of a simulation can be very complex to begin with. Agreeing with Marklund (2017), he urged the importance of understanding what is actually happening in the simulation model and what really affects the production system. Pehrsson (2017) noted that this is especially critical when there are multiple objectives to consider in a decision. He further strengthened his position arguing that it is more valuable studying how the underlying crude PMs correlate and interact then looking at an aggregated PM.

However, while Pehrsson (2017) was sceptical of using aggregated PMs for comparison, he acknowledged that they can be used for confirming that certain criteria are met, effectively using them as a screening tool. He furthermore confirmed that it can be valuable getting an insight of the system-wide effect by looking at aggregated PMs such as lead time and running cost, even in simpler operational decisions. Perceived isolated issues needs to be put into the context of the whole production system to provide the understanding of the correlations and interrelations between parameters in the system (Pehrsson, 2017).

Videsson (2017) was also sceptical towards the use of aggregated PMs. The issue he identified was that due to their detachment from the direct operational parameters, they may be hard to evaluate without being put into context. Exemplifying with lead times, he argued that while it is often a highly relevant PM, decision-makers may find it difficult to understand why decreased lead times is desirable.

4.2.2 Relativity

Wiklund (2017) further cautioned the use of relative PMs. He pointed out that while they might seem attractive, many people do in fact have trouble understanding what for example 10% reduced setup time really means. While relative measure aids the understanding of scale and proportion, absolute measures are closer to reality. Referring to the previous example, Wiklund (2017) suggested that it could be better to count the actual amount of saved time to use for other activities, or the actual amount of products produced per time period.

4.2.3 Lagging versus predictive

Pehrsson (2017) verified that PMs, which are normally considered to be lagging, can in the context of simulation output be predictive of the system performance. He explained that when simulating scenarios of potential future outcomes, it is indeed possible to analyse potential future constraints in the production system. By studying the effect of the scenarios on those parameters, Pehrsson (2017) argued that it is possible to mitigate the constraining factors and setup the system so that it is more robust to the future stochastic event spaces.

4.2.4 Automated generation

Pehrsson (2017) claimed that it would be valuable if some PMs would be automatically computed when doing simpler simulations. These PMs should preferably be a set of standard PMs which informs the user if the performance of the production system meets the criteria. Pehrsson (2017) argued that finding the correct PMs, preparing the data, and analysing it, can be too time-consuming in those cases. As a result, what PMs are used in practice are often constrained, he explained.

4.3 Simulation application best practice

This section will cover the views on how to best apply manufacturing simulation. First, it will recount the interviewees options improvements and investment as well as the use of bottleneck analysis. Next, their view on modelling and measuring quality and flexibility will be described. Last, it will include a discussion about the importance of aligning the simulation model and the performance measurement with the true purpose and the strategy.

4.3.1 Improvements

Pehrsson (2017) described that when initiating improvement projects, it is better to first use simulation to identify the true deficiencies and constraints in the production system. Doing a simulated what-if analysis straight away to find evidence for a claim risks deciding on a sub-optimal action. He considered it to be more advantageous finding the the true cause of the problem, rather than confirming or rejecting a specific scenario. Pehrsson (2017) cautioned that this is a common issue when initiating the endeavour of using simulation continuously, but noted that it is probably a necessary transition phase.

Regarding improvements, Marklund (2017) highlighted that one of the most valuable takeaways of simulating is building the model itself. The process of building the model requires a deep understanding of every logical detail in the production system. Hence, inefficiencies in the production system, which else might have been neglected, can be identified even prior to using the model (Marklund, 2017).

What is an efficient investment depends on the time-horizon of the decision, according to Pehrsson (2017). When making a decision based on the efficiency of an investment, it is better to consider a reasonable trade-off between a flexibility for future changes, running cost, and cost of investment, rather than looking at cash flows and net present value. Pehrsson (2017) warned that focusing only on the cash flow when making a decision risks constraining the discretion of taking the next decision. He argued that it is better to consider a composition of multiple PMs and assess them when making a decision. Pehrsson (2017) described finding a flexible investment as optimising against a solution that enables the discretion to take future actions, instead of optimising against what is currently best and might soon be outdated. Consequently, the flexibility becomes increasingly important, the longer the time-horizon of the decision. He argued that this approach will ensure long-term efficiency of the production.

4.3.2 Bottlenecks

Both Pehrsson (2017) and Marklund (2017) stated that simulation is best used for identifying bottlenecks in the production system. (Marklund, 2017) noted that the interesting dynamics to observe in a simulation model is the material flow; how buffers are growing, when they are growing, how it depends on the shifts in demand and the scheduling of the workforce. Bottlenecks can be effectively identified by investigating the *Japanese lake* [1] of productions systems, e.g. simulating lower stock levels or capacity (Pehrsson, 2017). According to Pehrsson (2017), the model he developed for analysing bottlenecks has been the most successful way of studying production systems using simulation. He emphasised that bottlenecks generally are the most costly factor of a production system and what limits growth. Identifying bottlenecks is equally important when not growing, as you want to be able to maximise the capacity you have dimension for (Pehrsson, 2017). Pehrsson (2017) further added that when reducing cost, you also need to reduce run-time and streamline the organisation to the current conditions by removing bottlenecks. Pehrsson (2017) concludes that enabling the identification of bottlenecks is an efficient way to find out what needs to be done, without spending much time or resources on modelling and other tools for analysis.

4.3.3 Modelling and measuring quality

Pehrsson (2017) remarked that DES is not necessarily the best tool to model quality. He argued that if the goal is to optimise quality parameters, then you should build a specialised quality model. A simulation model is for instance not the preferred way to analyse the cost of product quality deficiency stemming from experienced customer satisfaction, he exemplifies. Pehrsson (2017) suggested that rather than measuring the quality parameters themselves, it is more interesting to look at the quality deficiencies effect on the chain of events by measuring its direct impact on other parameters. He proposed looking at strategies for quality control, noting that if you can not fix a quality problem at its source, then you can analyse its impact on the production system.

Although, Pehrsson (2017) acknowledged that process quality can be effectively modelled in a simulation by adding scrap rates and its inherent stochastic. Wiklund (2017) highlighted scrap as highly important, and implies that this importance may be underestimated by many. Pointing out that it is preferably divided

[1] High inventory levels that hide the true problems in production such as bottlenecks and quality issues

into scrap from the continuous running of machines and scrap from setups and changeovers, Wiklund (2017) further noted the relation between scrap and batch levels [2]. Due to the random behaviour of scrap levels in each manufacturing process, the impact of the system scrap level is hard to forecast (Wiklund, 2017). Therefore, he argued that it would be highly valuable to model how scrap levels are affected by the batch sequencing and the performance of the machines.

Pehrsson (2017) further remarked that a simulation tool can be used to study strategies for quality control. Arguing that the goal is always to identify and correct the root cause of a quality issue, a simulation model can be used to investigate the effect of for instance additional inspections.

4.3.4 Modelling and measuring flexibility

Wiklund (2017) noted that there may be no obvious way to measure and quantify flexibility, although it could possibly be evaluated in a model implicitly by looking at some other measure. He suggested that by observing some other relevant measure (e.g. cost or delivery performance) while changing some variables (e.g. volumes, order deadlines or supplier lead times), then it is possible to get some insight of the flexibility of the production.

Pehrsson (2017) claims that evaluating the flexibility of a production system using simulation is mainly applicable in the form of stress testing different setups, i.e. analysing the limits of the system. He exemplifies this with testing the possible width of the product range. Agreeing on their applicability in simulation, Marklund (2017) regards such stress tests rather as measures of robustness. He further explains that flexibility in essence is connected to the time it takes to adapt to different circumstances. Therefore, measuring flexibility in a simulation model will revolve around time (Marklund, 2017).

Marklund (2017) considered volume flexibility to be the dimension of flexibility which is probably most easily measured in a simulation model. By observing the effects on constraints and bottlenecks of ramp-up and ramp-down in the production, measures can be done on the ability to meet changes in demand (Marklund, 2017). Measuring product mix flexibility can sometimes be done similarly as volume flexibility, according to Marklund (2017). Although, he added that besides only considering the constraints of the system as-is, there might be additional requirements such as investing in new machines. When measuring the flexibility, consideration must then also be taken into account on how much time it takes for the delivery

[2] Small batches leads to more setups, which leads to more scrap, and vice versa.

and setup of the machine (Marklund, 2017). Marklund (2017) explained that these kind of factors are harder to measure in a simulation model as they will require additional assumptions to be made as well as modifications to the model itself. Measuring flexibility in a simulation model is therefore easier when studying the effects on a factory with fixed conditions, i.e. when the structural properties of the simulation model are not changed (Marklund, 2017).

4.3.5 Aligning simulation with purpose

According to both Marklund (2017) and Pehrsson (2017), there is in principle no constraints in what you can simulate. The limitations are rather set by the complexity of modelling different aspects. Marklund (2017) however stated that in practice, modelling requires assumptions and simplification to be made. If this were not the case, the model would become just as complex and hard to interpret as the reality itself, he added.

When developing the simulation model, it is necessary to understand what the most important parts of the dynamics are in order to know what to make simplified assumptions about. The factors that are known to never constrain the system can be simplified to provide a less complex simulation model, without losing accuracy (Marklund, 2017). One of the benefits with simulation is the great flexibility of doing assumptions and not being constrained by mathematical tractability, Marklund (2017) notes. What are the most important parts of the dynamics is however not static, but depend on the purpose of simulating. Marklund (2017) therefore cautioned that, before initiating a simulation project, it is essential to know the true purpose of doing it.

Furthermore, when the simulation model has been developed, consideration must be taken into what to measure. What you can measure in the simulation model without making modifications is dependent on how general the model is, Marklund (2017) noted. He further explained that the inherent flexibility tends to result in the incorporation of unnecessary and irrelevant details when modelling simulations. However, as the model becomes more general, its complicity quickly increases, inflicting on the user-friendliness. To obtain the right information from the model, it is important to not just doing what you *can* do, according to Marklund (2017). Otherwise the decision-makers risk getting information overload. Therefore, it is imperative to be precise about the purpose of the simulation and aligning it with objectives of the user (Marklund, 2017).

Marklund (2017) underlined the importance of understanding that the simulation model is in fact a model, not the reality. An issue with simulation is that there are always events which can not be captured by the model, according to Marklund (2017). He exemplified with different production plans generated by simulation optimisation; they might have the same aggregated performance, but at the same time, they might be unequally attractive due external factors that the production planner knows about. Hence, Marklund (2017) argues that the final judgement about what is the best course of action can not be made by simulation. He further underscored that the simulation model will never by itself solve what needs to be done to improve the production system. Making the decisions, and suggesting actions on how to achieve a certain objectives, must ultimately be done by people with in-depth knowledge and understanding of the operations, claimed Marklund (2017). However, he still emphasised the value that simulation provides through decision support, learnings of the production dynamics, and understanding of the implications of decisions on various parameters.

4.4 Performance measurement in simulation

This section will focus on discussing what type of decision support a simulation should provide, and its implications on what is suitable to measure in a manufacturing simulation model. It will especially focus on the conditions of modelling cost together with a simulation model, including a discussion about potential benefits and pitfalls.

4.4.1 Selecting performance measures

From a general perspective, Videsson (2017), Pehrsson (2017), and Marklund (2017) agreed that what PMs are relevant depend on the strategic goals and the objective given the current situation of the organisation. Videsson (2017) exemplified by noting that whether the organisation operates with a pull or a push supply chain strategy will affect what is relevant to measure. Marklund (2017) remarked that if the manufacturing organisations are in analogous situations, their goals and objectives are in general similar. He continued with pointing out that there is always an inherent goal to increase efficiency in production. Therefore, while the specific PMs might differ, he claimed that there is a finite set of them which are relevant. Structuring the PMs by simulation application or a similar distribution is therefore perfectly reasonable as a general classification of PMs (Marklund, 2017).

Pehrsson (2017) and Marklund (2017) both confirmed that what is relevant decision support, and in extension what PMs are relevant, also depend on the type and level of the decision to be made. At the senior management level, the annual report and its inherent PMs are in focus, and for the factory manager, there are some aggregated PMs for the specific factory that is interesting, Marklund (2017) clarifies. These aggregated PMs may then be broken down into different PMs for production lines and inventories (Marklund, 2017). Consistent with the performance pyramid (see figure 7), Marklund (2017) noted that there is a hierarchy of PMs that on the top level aggregates into profit. By breaking down the profit into a set of PMs that steers in the same direction, he argued that they will collectively contribute to an improved performance either independently or through synergistic effects. Marklund (2017) exemplified that inventory turnover ratio and working capital can together create such leverage effects that will lead to increased profit. This holds true even without the use of simulation, he concluded.

What decision-support is needed and its relation to different decision levels is connected to what you simulate, according to Pehrsson (2017). While multiple PMs might be relevant for a decision type given the strategy and current objectives, simulation also brings a technical aspect to the selection process. Pehrsson (2017) argued that which specific PMs to chose also depend on the difficulty of modelling them. The desired PMs must be weighed against how complex the required data is to model (Pehrsson, 2017). Viewed from the opposite perspective, the operational level of the simulation model dictates what PMs you can look at. Videsson (2017) further added that there are typically multiple input parameters and only a few output PMs when simulating. This is partly due to that directly measuring the input parameters serves no purpose (Videsson, 2017). However, the main reason is that what is measured in the simulation model should be focused on the objective, according to Videsson (2017).

Marklund (2017) stressed that what is measured should be grounded in what you want achieve in the operations, and not in the simulation model. He insisted that there must be an in-depth understanding of the real operations to know what information is important for improving it and driving it forward. This is the key for selecting the right PMs, according to Marklund (2017). It is also important that the decision-makers know *which objectives are prioritised*, Pehrsson (2017) added. Ultimately, it is the preferences of the decision-maker that determines the weighting of different objectives. There are in essence only a few desirable PMs which are comprehensible and provides an understanding of what really happens (Pehrsson, 2017).

In slight contrast with Pehrsson (2017), Marklund (2017)argued that it is presumably not valid to claim that the selection of PMs is special for simulation. He claimed that simulation is just a tool for testing the effects of improvements, but what is measured in a simulation could also be measured in the factory. Furthermore, when evaluating the performance of an improvement after its implementation, the same type of operational measures would be relevant as when testing it in the simulation (Marklund, 2017). Explaining his standpoint, he stated that in the end, the same PMs must be implemented in reality as in the simulation to enable managing the operations according to them. Wiklund (2017) agreed, and further commented that when modeling with measures in general, it is important that they can be validated against real data.

However, Marklund (2017) added that it is possible to measure parameters in a simulation model which might be difficult to measure in reality. The major difference he pointed out was the time factor: Some impacts, such as a change in inventory levels, might take years in reality before their impact is noticed on certain parameters. Although, with simulation, these effects can be seen within hours. Simulation therefore makes it more convenient to follow up changes than in reality (Marklund, 2017). Furthermore, Marklund (2017) affirmed that the simulation model can facilitate the measurement of parameters that support the decision-making, but are neglected during implementation. On the shop floor, the complicity or resource demand of measuring these parameters might not outweigh the knowledge they contribute (Marklund, 2017).

Marklund (2017) further regarded simulation as a learning process, and that initially identifying the best PMs might be hard. Through experience, the increased understanding of what the simulation is capable of will aid the user in identifying PMs which were initially neglected (Marklund, 2017). However, Marklund (2017) stated that when this threshold of knowledge is reached, the user would most likely have found all the relevant PMs. Thereafter, the continued learnings will rather be about understanding the dynamics of how these PMs are affected by different decisions, he concluded.

4.4.2 Cost modelling and financial performance as decision support

This subsection covers the *external view* interviewees responses regarding cost modelling and the use of financial PMs (especially different aspects of cost) as decision support for manufacturing simulations. First, it describes the benefits, then the issues, and last, the alternatives to using financial PMs.

Why financial data might be desirable

Pehrsson (2017) noted that financial information is often desired when making a decision. He highlighted that including cost models can provide a huge support for adding credibility to capital budgeting when trying convince management on an investment decision. According to Pehrsson (2017), it would be outstanding to connect financial data to a simulation model if it is well documented, easy accessible, and transparent in the organisation. However, he pointed out that this is rarely the case.

Marklund (2017) considered cost to be an attractive PM to use for comparison. He described that when deciding between actions with different trade-offs, there is a risk of comparing apples and oranges. In order to compare different actions, Marklund (2017) claimed that there needs to be some kind of translation between their cons and benefits. He explained that one way of solving the problem is using a multi-objective optimisation with different weights which are connected to the simulation model. Another way is translating the simulated operational performance of the actions into monetary terms in a cost model (Marklund, 2017). When translating multiple performance dimensions to one, costing is the general approach in the industry, according to Marklund (2017). In the end, increasing the profit is what matters, he affirmed. However, he noted that an increased profit ultimately breaks down into the performance on different operational parameters.

Issues with cost modelling and financial performance measures

Although the arguments varied, there was a general consensus among the interviewees that costing has many pitfalls while its benefits are limited. According to Pehrsson (2017), finding the detailed data to map the operational costs is hard. Acknowledging the models developed by Jan-Erik Ståhl and his team, he confirmed that there indeed exists excellent, detailed economic models. However, his experience was that such models are impossible to use in practice, due to their extensive data requirements. In order to connect the economic data to the simulation, Pehrsson (2017) argued that either the models need to be more easily operated or approximations need to be found.

Complicity of setting cost parameters

Wiklund (2017) believed that there is no apparent and simple way to translate operational parameters and events into cost. Noting that it can be difficult to do in practice, he suggested that high utilisation rates for example can be priced using a factor representing the probability for overtime or a set of factors connected to master plan adherence. Wiklund (2017) added that setup times are often quantified in financial terms [3]. Although, he indicated that the accuracy of the estimate or assumption is usually not critical; it is merely some assumed cost of non-value added time. He further pointed out that setup time is not always the same as changeover time, and that the start-up scrap rates may also be different in the different cases.

Marklund (2017) agreed that it is generally hard to set costs on production events. Cost of sourced material and services is obviously well-known in an organisation, but the unit holding cost or the cost of quality in terms of goodwill and future effects are for instance much harder to determine (Marklund, 2017). He explained that adequately setting the cost parameters will therefore require much effort as well as maintenance to keep them up to date. Marklund (2017) stressed that if the cost parameters are not correctly validated, cost is a very dangerous PM to use for drawing comparative conclusions.

Marklund (2017) further cautioned that cost modelling is subjected to the concept of garbage in - garbage out. Wiklund (2017) alluded to this subject, explaining that cost modelling typically requires a set of assumed standard cost parameters. Knowing the true cost of some operational events can be difficult since they in turn may depend on multiple different factors which are hard to estimate (Wiklund, 2017). Marklund (2017) stressed the importance that the translation to cost is done properly, i.e. that the pricing of different parameters is not done arbitrarily. If the cost parameters are set more or less arbitrarily, it will result in arbitrary comparisons due to inaccurate skewness in the weighting (Marklund, 2017). He exemplified two cost parameters that are typically the subject of arbitrary cost modelling; 1) cost of setups, affecting the manufacturing cost, and 2) the holding cost rate, affecting the inventory cost. Wiklund (2017) continued on this list, exemplifying 3) stock-out costs, which are affected by lost sales, extra cost of express delivery, etc.

Marklund (2017) noted that if the evaluation of the actions are made using one specific cost dimension and the same cost parameter value, then one incorrect input parameter may not be an issue. The offset from the true parameter value will affect both scenarios proportionally [4]. However, if one cost PM is to be balanced against

[3] Quantifying setups in financial terms is for instance required for computing economic order quantity (EOQ).

[4] E.g., if inventory cost is the observed PM and the holding cost rate are equal for the scenarios

other PMs with different cost parameters, then it matters how these parameters are set (Marklund, 2017). Even if only one cost parameter is incorrect, it will affect the total cost and misrepresent the performance of the scenarios with potentially decisive impact, Marklund (2017) warned.

Usability of measuring the financial impact of improvements

Regarding modelling the financial impact of production improvements, Wiklund (2017) explained that it is typically dependent on the situation. He exemplified with the financial impact of an efficiency improvement generating higher throughput: Regarding the direct financial impact of higher throughput, there must exist a demand that can swallow it, otherwise it is not meaningful to calculate the value of the extra output (Wiklund, 2017). Nevertheless, Wiklund (2017) argued that an efficiency improvement can be beneficial indirectly even if it is not generating more sales immediately. He explained that it can generate free time for operators to do other things; in a Lean organisation this could for example be employee training or work with continuous improvement efforts. Concluding, Wiklund (2017) stated that saving time is always relevant to some extent, but mostly when occupation in the factory is high.

Pehrsson (2017) believed that, if the product range is small with few variants, the positive impact of an improvement could be measured with running cost by using the simulation together with a running cost model. However, if product range of the production flow is wider and more complex, he considered it better to measure the positive impact in terms of master plan adherence and minimum lead times. He concluded that the latter might even be better in both cases as it gives a truer and more straightforward depiction of the impact of the actions. If the actions makes it possible to produce efficiently in the system, then it is probably profitable in the sense of running cost as well.

Last considerations on cost

Marklund (2017) maintained that even if correctly translated financial PMs are implemented, they should still be used in conjunction with non-financial PMs. However, he made a final point regarding the benefits of using costing with a simulation model. By analysing both financial and non-financial PMs of simulations, discrepancies from the real-world impacts can be made visible (Marklund, 2017). This setup can be used successfully to identify incorrect cost parameters used both inside and outside the simulation model, according to Marklund (2017).

Last, Marklund (2017) declare that monetary terms are generally not preferable to measure on the shop floor, but rather quantities, time, availability and other parameters that can be physically measured. Transforming such operational measures into financial measures and indicators will generate great uncertainties in how they are actually quantified (Marklund, 2017). Pehrsson (2017) summarised by stating that cost models are often not necessary; it is often quite straightforward knowing whether or not a decision is profitable by studying the operational measures.

Alternative to modelling cost

Rather than using an inadequate translation to an aggregated financial PM, Marklund (2017) considered it better to focus on operational measures and weigh PMs of different dimensions by mapping out their interrelations.

Pehrsson (2017) noted that the manufacturing objective is always the same; produce what has been planned or ordered with the minimum resources. Instead of looking at aggregated cost, he argues that it is more effective to analyse bottlenecks and other constraints in the production. According to Pehrsson (2017), you can always assume that if you lower your WIP, you will lower working capital. If the production works according to plan, efficiency is not lost (so that run-time needs to increase) and deliveries are done in time, then removing constraining factors in the production will always be the most profitable option (Pehrsson, 2017).

Relating to simulation, Pehrsson (2017) explained that you can simulate what-if scenarios, or optimising towards minimising and redistributing buffer space, to achieve a lean buffer capacity. This will result in an efficient production system with minimised working capital as well as revealed constraining factors. Working in parallel with bottleneck analysis will therefore ensure optimal efficiency given the current conditions, according to Pehrsson (2017). This will in turn always have an indirect positive impact on the financial parameters (Pehrsson, 2017).

Chapter 5

Conceptual Analysis

This chapter will analyse the conditions for decision support and performance measurement in manufacturing simulation. The basis of this chapter are the findings from the theoretical view and the external view. The chapter will cover both analysis and discussion on the material from each view separately and conjointly, highlighting both agreements and disagreements between the views. Furthermore, it will present the authors view on the topics, including inferences made and additional considerations.

5.1 Simulation and decision-support

The section will discuss how a simulation model and its corresponding PMS should be designed to provide decision support, by facilitating knowledge creation. It will cover the relation between simulation-based decision support and the knowledge pyramid, and present potential pitfalls of simulation models.

5.1.1 Simulation and knowledge creation

Simulation and its application in manufacturing can be viewed from many different perspectives; this study has so far presented some of them in for example table 7 and section 3.3.4. In the view of simulation as decision support, whether in a Decision Support System (Decision Support Simulation System) or on its own, it can be connected to the knowledge-based view of decision-making. Figure 12 below proposes the role of simulation in this view.

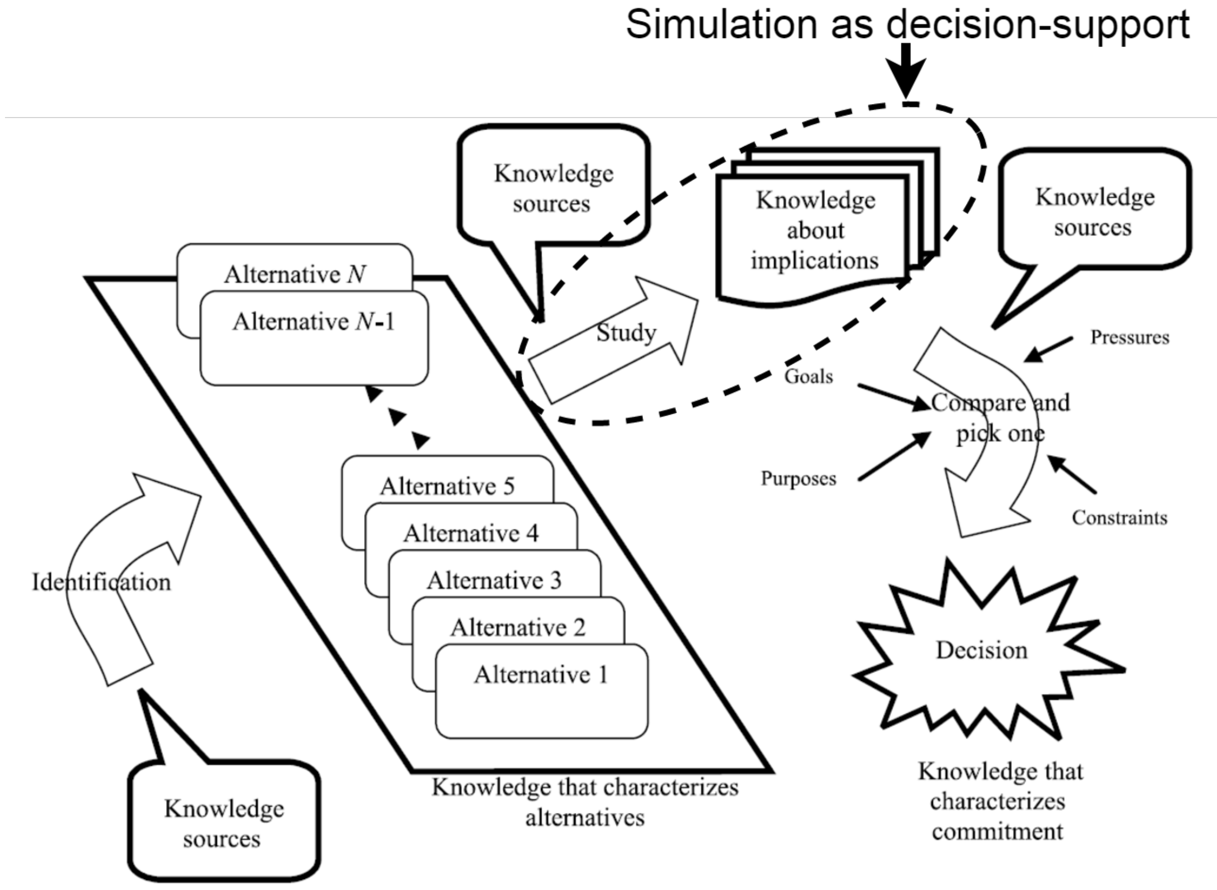

Figure 12. Simulation as support in knowledge-based decision-making. Based on (Holsapple, 2008)

As discussed in section 3.1.1, one step in the process of arriving at a decision regarding a set of alternative actions (or courses of action) is to evaluate their implications. Simulation can be a tool for that, as shown in figure 12 above. The question remains, however, how such implications should be described in order for the decision-maker to be able to compare them and ultimately arrive at a decision.

Since the decision-maker compares the alternatives' implications on the basis of purpose, goals, constraints and pressures, it appears a reasonable claim that the simulation-based decision support should in some way be connected to these. Connected to the pressures, the information it provides should be relevant to the individual decision-maker's situation. Regarding purpose, the purpose of making a decision in a certain decision area, should be the purpose of simulating. The information that the simulation tool provides, should also be aligned with organisational- and/or individual goals in a certain decision area. Finally, for the constraints that the decision-maker faces, the simulation-based decision support should indicate whether they are violated or not, or at least provide the information needed to evaluate that.

In extension, any form of decision support, including simulation-based, should provide information aligned with the four considerations above. If for example:

1) cost reduction is an important goal;
2) keeping costs low is an objective or a pressure on the decision-maker;
3) low cost is in fact a constraint; or
4) the purpose of making a decision in the first place is to lower (or keep low) cost,

then the simulation-based decision support should include these aspects. Either by effectively evaluating them, or at least by providing knowledge on *how* they are affected.

Decisions in this view are per definition based on knowledge, or more specifically the "progression of knowledge". It therefore follows that simulation in the form of decision-support should in some way facilitate this progression. A modification can be made of figure 4 on page 37, highlighting the role of simulation in this progression.

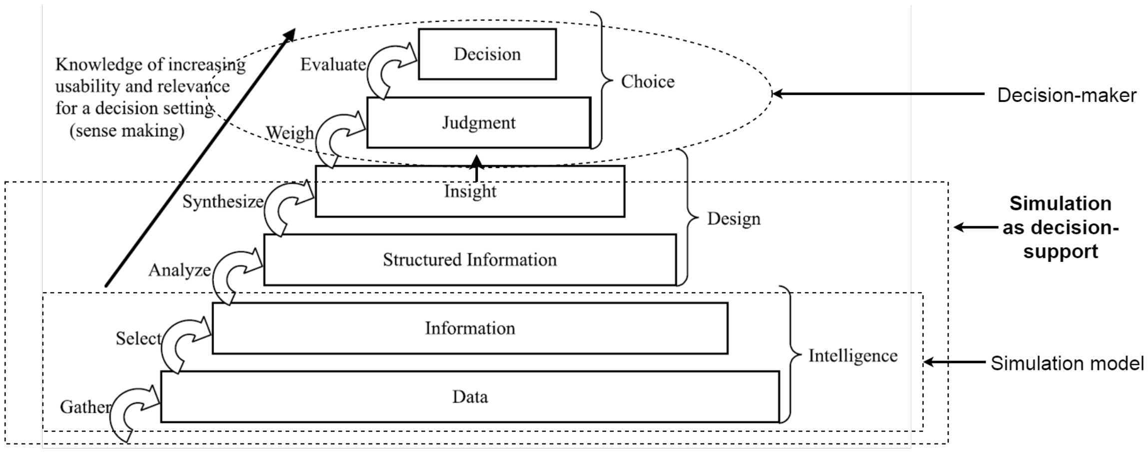

Figure 13. Simulation-based decision-support in knowledge progression. Based on Holsapple (2008) (In turn based on Simon (1960), Van Lohuizen (1986))

In figure 13, it should be noted that it cannot be universally and exclusively postulated which roles in the knowledge progression that a simulation model in itself, or a DSSS, can and should have in different cases. It depends heavily on what type of simulation model that has been developed, as well as what the decision-support tool is designed to be. However, the simulation model in itself is merely a technical application which generates and gathers *Data* on a variety of different variables. The simulation model's output could in extension be referred to as selected *Information* in the knowledge progression.

In order for a simulation application to provide any progression in the knowledge states, and thus constitute actual decision-support, a reasonable claim is that it should encapsulate more of the knowledge progression by itself. Merely generating data or information in large quantities, is not likely to support the decision-maker. On the contrary, it might even subject him/her to *information overload*, as discussed in section 3.1.1, and through that instead preclude any decision from being made whatsoever. The decision support tool could therefore facilitate the step of analysing the information into *Structured information* and possibly also synthesise it into *Insights*. However, as was deduced in section 3.3.7, simulation is in principle not a decision-maker in itself and a decision-support tool is probably not able to move any further than the Design phase on its own. At a reasonably complex level (e.g. without Artificial Intelligence), it is not capable of providing any *judgement* on the insights nor making the actual *decision*. In other words, the technical application should meet the human decision-maker somewhere half-way in terms of creating the knowledge required to make a decision.

5.1.2 Simulation, learning and understanding

The application of simulation as decision-support in knowledge-based decision-making can be seen as condensing data on the manufacturing system's performance in a certain simulated scenario, into relevant decision-support. This is therefore mainly concerning how to measure the implications and how to present them to the decision-maker. However, this type of scenario evaluation only captures one of the benefits of using simulation as decision-support highlighted by Semini et al. (2009) in section 3.3.2. The other benefits revolve more around how simulation can improve *understanding* of the real manufacturing system and how it can be used as an analysis or communication tool.

In the external view on simulation, Marklund (2017) suggested that the perhaps best way simulation can be used as decision-support is to create understanding of how the system's dynamics work to affect performance. He also noted that the process of building the model itself often creates a large portion of that learning. This was much in line with Pehrsson (2017), who claimed that bottleneck analysis in his experience appears to be the perhaps best way to use simulation as decision-support.

It can be concluded that evaluation of alternatives is not the only way to apply simulation for decision-support, and perhaps not even the application with the highest potential benefit. Instead of merely showing the decision-maker the performance of the manufacturing system in one specific scenario, with one large set of specified input parameters on a few performance objectives, simulation might be able to provide insights as to which parameters to adjust in order to improve. Marklund (2017) noted that simulation in the end is not able to provide the final answer on the most appropriate course of action, but as Pehrsson (2017) suggested, it might be able to reveal the true causes of issues and the improvement areas with the highest potential. It has also been shown in literature that structured methodologies such as the Theory of Constraints and philosophies such as the Japanese lake effectively can be applied through simulation. The synergies not only regard the automatised detection developed by Pehrsson (2013), but also through the fact that the systematic but sometimes experimental approach can be applied in a virtual environment and not on the real system.

5.1.3 Aggregation, integration and modelling issues

After considering the role of simulation in the knowledge-based view of decision-making and knowledge progression, one should consider how to go from a simulation model generating data or information, to a useful decision-support tool.

Given that the decision-maker would select the alternative with the best overall performance in his or her decision area, one way could to be through **Aggregation**. This would mean increasing the relevance by aggregating the performance data on several areas in the simulated system, into one or a few overall performance measures. In other words, aggregation can also be described as the amount of output parameters per the amount of input parameters. This type of aggregation can in principle be in two forms; *Information aggregation* and *Time aggregation*.

Information aggregation describes to what extent the DSSS is holistic and bundles performance in individual parts of the simulated system into some form of overall performance. The decision-maker is likely to be more interested in whether the performance of the whole simulated system is high or low, rather than whether several individual parts are.

Time aggregation refers to whether the DSSS tool generates few or many evaluations of performance in the simulated time period. An example could be whether it shows the average occupation in a buffer, or its development over time. A decision-maker could be more interested in one or the other, or they could both be important.

When building the simulation model, one should also consider what "overall performance" really entails. This can be described as the level of **Integration**. Integration can further be described in two different dimensions; *Vertical integration* and *Horizontal integration*.

Vertical integration refers to the inclusiveness of the simulation model. In extension it describes how much of the actual system that the decision-support tool considers. A reasonable level of vertical integration means considering an adequately large part of the actual system, in the simulation model from start. Again, the decision-maker may be more interested in whether the performance of the whole, *actual*, system will be high or low, rather than whether the performance of the *simulated parts* of the system is.

Horizontal integration refers to what dimensions or types of performance the DSSS considers. This is related to the objectives and dimensions of performance in the simulated system, that the decision-maker is interested in, and thus what the decision-support tool should capture.

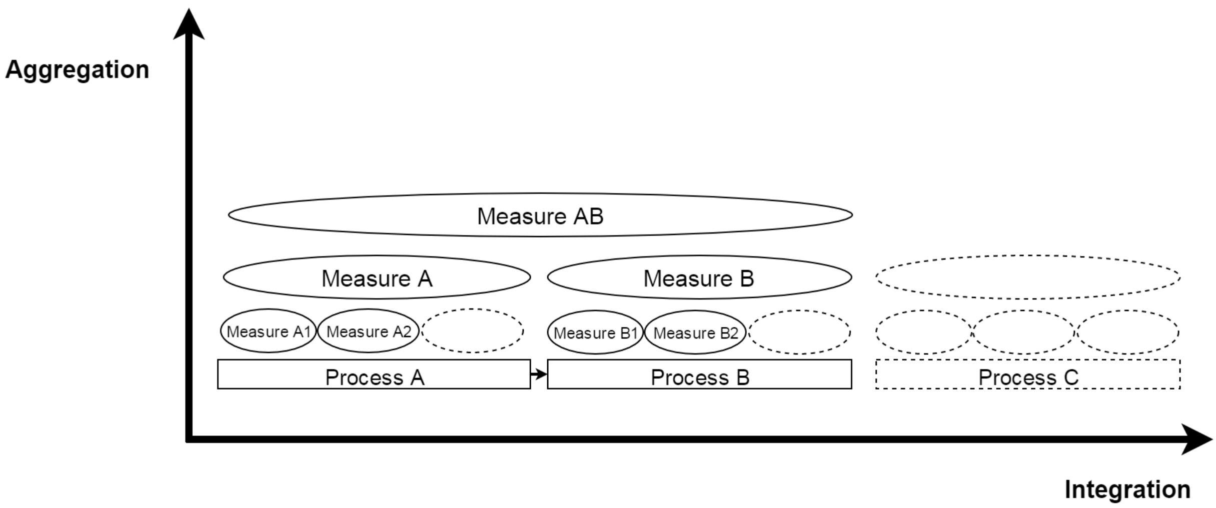

Figure 14. Aggregation and integration of measures and simulation model in a DSSS

Figure 14 above shows the principles of aggregation and integration by exemplifying two consecutive processes with an arbitrarily large set of performance measures on each.

The third process, which in reality follows after them, might be affected by the performance of the previous two, but is not included in the model. The boundary of the vertical integration is thus set around Process A and B. The number and types of measures used on the simulated processes describes the horizontal integration. The level of information aggregation is to what extent several measures are aggregated to a few in the DSSS tool. The level of time aggregation can be described as whether the measures reflect some average over the whole simulated time period, or several sub-periods, or single, continuous snapshot-measures of the system performance over time.

Translation

It should be noted that the measures A1, A2, ..., in figure 14 are not necessarily the same type of measure (e.g. time, cost or efficiency). Furthermore, Process A may be completely different from Process B, as they for example could describe a production line and a warehouse. Therefore, the measure B1, B2, ..., could also be completely different from A1, A2, ..., etc. The implication of this is that in order to aggregate the measures A, B and AB from their respective components, one would need to find a **translation** between them. If they are closely related, then the translation could be quite straightforward. If they are for example average machine utilisation and service level respectively, it is most likely more difficult. This will be further discussed in section 5.2 below.

Integration and objective alignment

The level of integration determines *what* the DSSS tool evaluates, and on what attributes. Therefore, in order for the decision-maker to effectively be able to make a judgement about what the tool presents, it is important that the level of integration reflects his/her objectives. If the decision-maker is interested in improving the productivity, while keeping WIP and inventory low, the level of horizontal integration should cover these measures. In terms of vertical integration, it is not enough to set the boundary only around a production line, it also has to consider the warehouse. The need for aligning the simulation model with its purpose and the objectives of the user was firmly stressed by both Pehrsson (2017) and Marklund (2017). If these are multifaceted, the level of integration becomes higher, as well as the amount of data and information within the model. In order to avoid information overload, a higher level of integration is likely to require more aggregation as well.

The integration trade-off

Despite the need to capture all of the decision-maker's objectives, a high degree of integration could become problematic, as the scope of the simulation model would increase. As Robinsson (2015) has shown, not only would this increase require substantial effort while giving small payoff in model accuracy, at some point the accuracy might deteriorate completely. Another issue is where to draw the boundary of what peripheral parts of the system to include. Although the decision-maker might have a clearly defined area of responsibility, it can be questioned why he or she should ignore the effects that changing the system might have on other parts of the Supply Chain. Looking too narrowly may cause sub-optimisation and/or silo thinking (see section 3.2.5), but the boundary nevertheless has to be drawn somewhere.

The aggregation trade-off

Aggregation can to some extent be described as a question of what the DSSS tool ultimately should do with the data that the actual simulation generates. If the simulation model generates a time-log of virtual products entering and leaving a modelled warehouse, one aggregation would be the average inventory level. If the modelled system consists of several warehouses and buffers, a further aggregation could be the total average amount of inventory or WIP in the system during the simulated time period.

From the external interviews, some scepticism was however expressed towards a high degree of aggregation as basis for evaluation (Pehrsson, 2017), (Marklund, 2017), (Videsson, 2017). It appears that aggregation in itself may conceal what the actual issues are in the system, as well as detach the evaluation from the actual behaviour of the system. Pehrsson (2017) noted that aggregated measures should function as *criteria* in solution screening, rather than evaluations for comparison of alternatives.

Regardless of whether the aggregation is made in the form of cost modelling/financial measures or some operational measure, it seems to be the subject of a trade-off. On one hand, it appears to be desirable and to some extent necessary in order to provide a progression in the knowledge states, and thus provide usable and interpretable decision-support. On the other hand, aggregation seems to have the drawback of a loss of detail. A loss of detail in a DSSS can have at least two consequences.

First, it hinders one of the benefits of simulation highlighted by Semini et al. (2009) as well as expressed by Marklund (2017) and Pehrsson (2017); namely the learning and understanding of system behaviour.

Second, it risks making a decision-support tool something of a ”black-box”. The more processing the application does of the simulation data and the less it shows of the actual simulation process, the more questions the decision-maker is likely to raise regarding its accuracy. That is, the *perceived credibility* of the DSSS tool outputs could decrease. Particularly in the case of cost modelling, the actual accuracy in itself also risks being low, due to the complexity of building, validating and maintaining such a model (Pehrsson, 2017), (Marklund, 2017). Conclusively, depending on how the aggregation is done, there might also be a loss of *actual credibility* if reality proves the model wrong.

5.1.4 Summary

With the knowledge-based decision-making model as basis, one should consider both the level of aggregation and the level of integration when using simulation as decision-support. In principle, it appears that:

1) High degree of integration is difficult to achieve and may lead to losses of accuracy due to complexity
2) Low degree of integration may lead to sub-optimal decisions and silo-thinking
3) High degree of aggregation may lead to loss of credibility, understanding (black-box) and learning
4) Low degree of aggregation may lead to information overload and loss of decision-support relevance

Figure 15 is proposed for visualising how aggregation and integration should be considered jointly, with respect to the identified issues listed above.

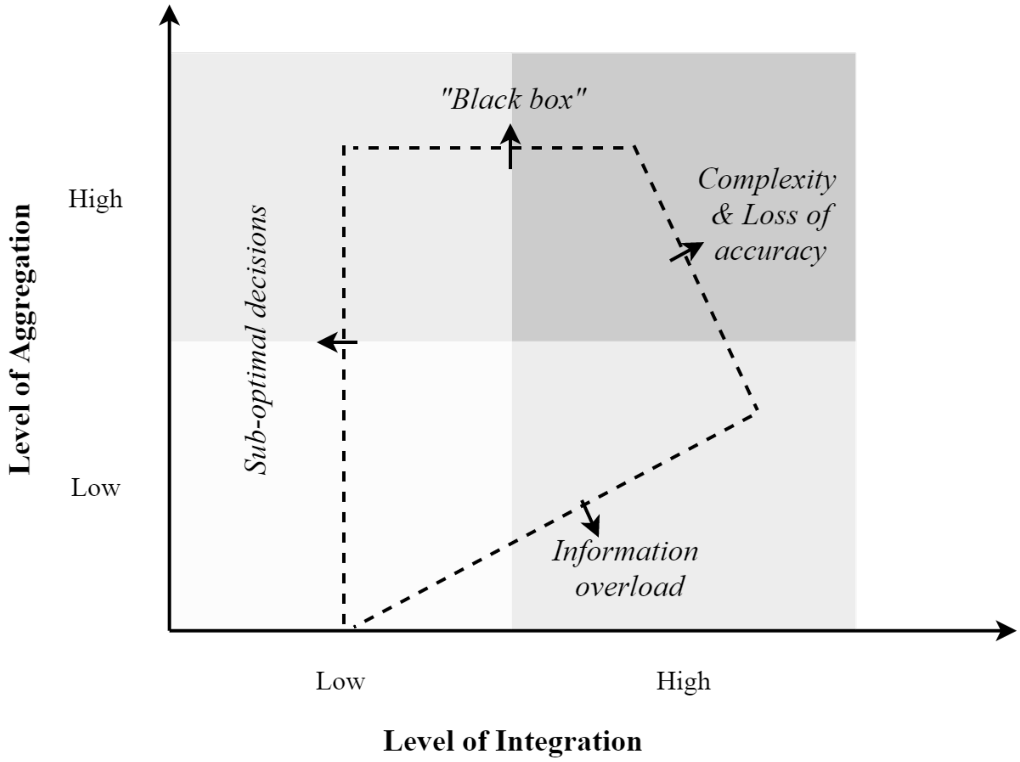

Figure 15. Aggregation-Integration Matrix (AIM). A mapping matrix with integration and aggregation as separate dimensions.

5.2 Measuring manufacturing performance in a simulation model

The key difference between performance measurement in a real system and on a simulation model is the conditions for measurability. The technological properties of a simulation model offer both limitations and possibilities in terms of measurability. The three significant differences between the performance measurement in a simulation and in real systems are the factors of time and resources and measurability due to modelling complexity. In the following part of the section, these differences as well as their implications will be highlighted and discussed in detail.

5.2.1 The time factor

The arguably most important difference in measurability is that reality is subjected to time; without a forecasting tool, it is not possible to measure what has not yet happened. It is however possible to look backwards and draw inductive conclusions on what will happen in the future based on historical outcomes, although it is impossible to be sure that history will repeat itself. Furthermore, the reliance on historical data only takes you that far; if you want to predict what will happen under new conditions or during unprecedented events, then the historical data will not be sufficient. Due to the complexity of a manufacturing system, with its inherent stochastics and tangled interdependencies, it is practically impossible to make any accurate predictions without an advanced forecasting tool.

On the other hand, a simulation model can effectively predict and measure future possible outcomes, as it is able to manage the manufacturing system's complexity. It is however important to note that a simulation model is not a time-machine. It can only predict what is *likely* to happen given the conditions that are modelled. Hence, the more accurate the model, the better the prediction. The trade-offs between accuracy and complexity is discussed in section 3.3.3. However, as Marklund (2017) noted, simplifications can be made on factors known to never constrain the system performance without loosing accuracy. Nevertheless, as Marklund (2017) pointed out, the simulation model is a only model, and will never reach an accuracy that truly represents reality. Furthermore, the manufacturing system operates in an external environment, which will lead to events happening which the model cannot take into consideration.

Besides the possibility of measuring potential future outcomes, the time factor gives rise to questions regarding the tense of the PMs. Are PMs lagging or predictive when they are measured as future outcomes in a simulation model? According to Pehrsson (2017), normally lagging PMs can indeed be considered to be predictive when applied on the output of a simulation. Moreover, if they can be considered as predictive, the historical critique against financial PMs for being lagging (Parker, 2000) is arguably invalid when applied in a DSSS. This opens up for a higher relevance for financial PMs when designing a PMS for the DSSS. However, the critique that financial PMs often are very insular and inward-looking, as well as missing to include less tangible aspects (Parker, 2000), is not mitigated by the change of tense.

The claim that outcome PMs can be considered as prognostic in a DSSS should not be misinterpreted as that they make predictive PMs redundant. The outcome PMs are only prognostic of what potentially will happen in the simulated time-frame, not of what happens thereafter. It is possible to argue that if it is desirable to study what happens after the simulated time-frame, one can just do another simulation with a longer time-frame. However, returning to the issue regarding the accuracy of the model; the further you simulate in the future, the greater will the impact of the discrepancies between the reality and the model be. When accuracy is of relative high importance, these discrepancies will matter, rendering the simulated far future outcomes unreliable. Simulating over a long period is not even applicable in all cases; for instance, when simulating a production plan stretching over two weeks, it is not meaningful to look further in time than the plan itself. However, measuring predicative on the implications on for example the next production plan might still be important. Predictive PMs may also be used to illuminate the progress of reaching objectives which might be far away in the future, which might be highly pertinent on short-horizon simulations (Melnyk et al., 2004).

5.2.2 The resource factor

Marklund (2017) commented that what is relevant to measure in a simulation model is equivalent to what is relevant to measure in the real system. While this might be true, what is relevant to measure does not necessarily correspond to what can practically be measured. The data which can be measured in a real system is in practice limited by the organisation's resources, as it requires physical equipment or actual people to measure all data (Marklund, 2017). The consequence is that what PMs are used in the real system must be prioritised by weighing their individual benefits in terms of knowledge contribution against the cost of measuring them (Neely et al., 1995).

A simulation model does not require physical measurement, and is therefore not subjected to the limitation of resources. On the contrary, it is possible to measure every operational parameter included in the model automatically with the press of a button. As a result, the relevant PMs which in the real system are neglected due to the complicity or cost of measuring them, can be measured in a DSSS. This implies that the only consideration to what PMs to select is their benefit.

While this is theoretically true, the complexity of accurately modelling certain aspects and parameters in the manufacturing system renders the notion practically false. The selection of PMs for a simulation model hence becomes a matter of balancing the individual benefit of a PM with the complexity of modelling it, rather than considering the cost. It is however important to note that no matter how high the perceived benefits are, some aspects are extremely complex to model in a DES. In practice, there will always be aleatory uncertainties and external factors which are excluded in the model. This is often due to that they are so complicated to understand and measure in reality, that there is no reliable data to model on.

5.2.3 Measurability of performance dimensions

This section covers an analysis of the measurability of the manufacturing performance dimensions; cost, quality, delivery and flexibility. It will discuss general findings and point out what subdimensions are appropriate to model and hence to measure in a simulation.

Cost performance

Cost performance is the primary competitive priority in more or less all manufacturing organisations. This undeniably makes measuring cost performance a high priority. There has been major criticism on the use of financial PMs[1] in PMSs. It is however important to point out that this criticism is directed towards relying to heavily on them, due their characteristics of being inward looking, exclusive of intangible aspects and lagging[2] (Parker, 2000). It is undisputed that financial PMs are necessary in an organisation's PMS, and their ratio should be in balance with non-financial PMs. In any for-profit corporation, financial performance can be considered as the most aggregated measure of performance, and the ultimate objective (Marklund, 2017). Therefore, financial measures are typically desired by decision-makers (Pehrsson, 2017).

The suitability of financial PMs do however depend on the level of the decision-maker; it is more important at strategical level decisions than at the operational level. The basis of this difference is obviously related to the responsibility areas connected to the different decision levels. Recollecting the performance pyramid (see figure 7 on page 45), the financial performance area is located at the business unit/factory level. It is generally the business unit top managers that have financial objectives towards the corporate head-quarters, and as such have incentives of using financial measures.

The aim of this study is however to determine what benefits and issues are equal and what differs for the real world practice of performance measurement and in a simulation-based decision support. Cost modelling has been highly favoured by the advancement of DES, although, it still remains a highly complex and difficult matter. Furthermore, using cost as a means of evaluating the manufacturing system performance of simulated scenarios has been questioned. Cost has been questioned

[1] When discussing financial PMs in the context of simulation, different measures of cost is generally what is intended. Therefore, the two concepts will be used interchangeably.

[2] Recalling the discussion on the time factor in section 5.2.1, the criticism of financial PMs being lagging is not valid in the context of simulation.

on two fronts; both for the properties of financial measures and for the difficulty to model cost in a reliable way. In the following part, these two fronts will be analysed and discussed in greater detail.

Financial performance measures

It appears that given a valid cost model, generating aggregated financial measures in a simulation, can provide valuable information to a decision-maker in evaluating the results of a simulation. However, although financial measures are highly relevant as decision-support, several issues arise:

1) they are subjected to the aggregation trade-off;
2) they may conceal the actual issues in the operations; and
3) the knowledge they provide is blunt, even if they are accurate.

Regarding item 1), the key benefit of using cost PMs is that they are understood by everyone in the manufacturing organisation. Furthermore, not only is it best practice, but cost is arguably the only performance dimension to which all other dimensions can be translated to (to a certain degree) on the bottom line. Hence, it can be used to effectively compare different scenarios with different conditions and performance trade-offs. These benefits are all due to the aggregation of cost PMs. There are however several negative consequences with cost due to the aggregation. This is especially the case when considering the use of a total cost PM. While cost itself is universally understood, it is arguably important to understand *what* costs. Not only does a too aggregated cost PM hide what drives the cost, it also prevents the identification of costs that might be more easily mitigated than others.

As pointed out in item 2), the aggregation of cost, and especially a dominant focus on cost PMs, conceal *why* processes cost. Even a valid cost model is not perfect, and it should not be expected that a cost model will generate cost predictions that necessarily are realised. Without knowing the background dynamics of the cost PMs, they will lose credibility when the forecasts do not match outcome. The essence of both item 1) and 2), is that cost PMs risk damaging the understanding of the manufacturing system, which according to Marklund (2017) is the key benefit of using a simulation model. One should therefore consider carefully what the level of aggregation should be. It is clear that some level of aggregation is needed and a way around the aggregation trade-off could be to extract, process and present both aggregated measured and non-aggregated measures. That way, the decision-maker can see both an estimate of the overall performance as well as the dynamics leading to it. This is much in line with the suggestions of both Pehrsson (2017) and Marklund (2017).

Furthermore, despite being highly relevant evaluation criteria, financial measures should be used jointly with operational measures according both to theory (see section 3.2.4), Pehrsson (2017), and Marklund (2017). The combination of financial and non-financial PMs have synergistic benefits. As concluded, profit is the long-term goal of all for-profit organisations. Every process, action and decision will eventually have a financial effect on the bottom line results. By gaining an understanding of how they impact reaching the goal is highly advantageous. However, consideration should be taken so that the use of cost does not lead to short-termism in reaching cost reductions at the expense of long-term cost performance. Last, item 3) is closely related to the limitation posed by cost modelling, which is discussed in the next part. It mainly regards the fact that financial PMs do not consider less tangible aspects such as customer satisfaction, goodwill, and multiple flexibility aspects.

Cost modelling

There are two basic facts that need to be considered when regarding validity of a simulation-based cost estimation:

1) a simulation model can not represent reality in full accuracy; and
2) a cost model can never represent the true costs in full accuracy.

The bottom line is that a simulation-based cost model will never produce a fully accurate prediction of the true costs. When the simulation model is lacking in accuracy, the aggregation property of cost can result in that the inaccuracies of the cost are leveraged. Even if the cost model is accurately modelled, a crude simulation may still distort the cost PMs to a degree that the accuracy of the measures are too insufficient to be used constructively.

The difficulties of accurately modelling cost can be summarised to be that they:

1) require a large amount of accurate input data;
2) are difficult to build;
3) are difficult to validate; and
4) are difficult to maintain.

Concerning item 1), it is a shared property among all cost models that they require large amount of data, which can make them practically too complicated too feed to be valuable (Pehrsson, 2017). However, the problem with accuracy might be just as big a problem. It is crucial that the input parameters are correct for the model to be valid. A possible solution to easily obtaining financial data would be to integrate the model with the organisations ERP system or some financial system.

While this might solve the problem, the integration might be technically complex, if not impossible in many cases.

What is an input parameter to the cost model varies, as the parameter might itself be modelled and it is rather the parameters' components that are the inputs. If an input to the model requires prior modelling and estimations, such as setup cost and holding cost rates, then it is crucial that they are done accurately. Feeding the model with inaccurate data will result in inaccurate cost estimation, that might have critical effects on the decision-maker's evaluation (Marklund, 2017).

The issue with correct input parameters is connected to item 2). Even if the inputs are fairly correct, it all comes down to how the model is built. The main difficulty of building the model is allocating the overhead costs and other factory expenses (Marklund, 2017)(Wiklund, 2017). How this is done differs greatly between different cost model approaches, however the trend is towards derivatives of TDABC, using time as the main driver of cost. This is arguably a valid strategy when organisations are implementing a Lean philosophy. While possibly more accurate approaches of tying indirect costs to products exist, such as the use of machine learning and neural networks, they are also much more complex to build. Nevertheless, all cost models have their pros and cons, and it is easier to argue that some models are poorer than others, rather than stating which one is the best. What cost model to finally use is also dependent on the simulation model, as it must include all the input parameters required for the cost model.

Regarding item 3), the issue with validating a cost model largely stems from the issue of overheads and factory expenses as well. How indirect costs are affected by an action can seldom be accurately traced due to the complexity of the manufacturing system. There are furthermore many intangible effects that neither the simulation model nor the cost model can capture in a satisfying way. Finally, concerning item 3), the cost model is difficult to maintain. Just as with the simulation model, the cost model needs to be kept updated to be valid. This regards both keeping the input parameters updated, but also the model itself when processes in simulation model changes. The maintenance of having the right costs for material, depreciation etc. requires continuous work if not automatically updated, e.g. by integrating an ERP system to the cost model.

Concluding remarks

A conclusion is that cost is a highly sought after PM, with high relevance for manufacturing organisations and with multiple benefits regarding its usability. However, the applicability of cost PMs stands and falls with the quality of the cost model and its input parameters. If the quality of the model or the input parameters are failing, then cost and financial PMs should not be used as a basis for evaluation of manufacturing simulations.

However, a crude cost model might arguably still be valuable as a means of gaining a holistic understanding. If the model is simplified so that it is mainly based on prime costs that can be more easily validated, the cost model can serve as a tool of providing a sense of the cost proportions of different actions and decisions. An "in the ballpark" estimate of the cost can hence be highly valuable in bridging the understanding between the operations and the finance department, as well as making lower level managers more aware of the cost impact that their operational decisions have.

Quality performance

Out of the two subdimensions of quality, i.e. product quality and process quality, it is the latter which is more suitable to model and hence measure in a simulation model of a production system (Pehrsson, 2017). Modelling product quality is hard and requires consideration of external factors such as experienced customer satisfaction. While measuring the performance and features can be done objectively, those measures do not serve any purpose when evaluating the manufacturing performance. The effect that the product quality in terms of reliability and durability has on goodwill, and in extension on future sales, could be included in a simulation model. The effect on demand could be included in a forecasting demand model connected to the simulation model, or by modifying the demand distribution. However, the estimation of the impact of goodwill is likely arbitrary, and largely based on assumptions.

A simulation model can however be effectively used to measure process quality. The main application of measuring quality performance in a simulation model is by studying internal failure, such as scrap, rework and waste (Pehrsson, 2017)(Wiklund, 2017). Scrap levels are of major concern in modern manufacturing organisations, both for reducing costs and waste reduction; the latter being a key theme of Lean for increasing the production flow. It is however important to note that the scrap level distributions are input parameters in a simulation model. As such, if the scrap rates are modelled with one-state distributions, the scrap rate will only be dependent on the processes throughput, and the value of measuring it rather limited. If the scrap rate distributions are different for different product types, then another dynamic will be added as the product mix will affect the scrap levels as well. Furthermore, if multiple-state distributions of the scrap rates are added, differentiating between continuous running, setups and changeovers, then the scrap levels also become dependent on both batch sizes and scheduling. The true value of simulating scrap levels arises when it reaches the level of complexity including multiple dependencies. Due to stochastic behaviour of scrap levels, predicting how dependencies such as batch sizes affect them is highly complicated in reality. On the contrary, modelling scrap rates with flexible distributions, as well as rework and waste, can be quite easily adapted into a simulation model, making it an excellent tool for measuring quality in terms of internal failure.

Pehrsson (2017) also recognised the possibility of studying quality control strategies in terms of product appraisal in a simulation model. This can for instance be done through what-if analysis by measuring the impact on the internal and external failures of inserting additional inspections, calibrations or tests in the model. Hence, it is very much possible to observe the effects of multiple dimensions of process quality in a simulation model. Although, if the aim is to optimise the process quality, it is better to use a specialised quality model than a general model of the manufacturing system. A DES quality model is furthermore not necessarily the best option (Pehrsson, 2017).

According to the literature, process quality is generally measured as number of defects (mean time between defects) and cost of quality, or by using techniques and methods associated with SPC and Six Sigma. Rather than directly measuring the quality performance in a simulation model, it might be even more interesting to measure its effect on other parameters (Pehrsson, 2017). Scrap levels affect the amount of waste and number of reworks in the system, thus having an immediate effect on the throughput rate of the processes and workflow variability. In turn, this affects manufacturing cycle time, master plan adherence, inventory levels, etc., ultimately affecting the cost performance, delivery performance, and flexibility performance. Depending on the objectives and the competitive priorities, process quality might therefore be more interesting to study indirectly in terms of other performance dimensions.

Delivery performance

Measuring the delivery performance in a simulation model is similar to measuring it in a real system. However, this is only true to an extent. The basis of this claim is that manufacturing performance only represent one side of delivery performance. The other part, i.e. the distribution of the products from the FGW to the customer is not covered by it. While it is perfectly possible to simulate the distribution of goods, it is preferably done in a special model. Including distribution in a model for the manufacturing system makes it too complex, at least if the purpose is to observe the processes in some detail. Hence, the measurability of delivery performance is not limited by simulation in general, but rather by a simulation model of a manufacturing system. In the end, it is possible to argue that the loss of the external perspective renders delivery performance less important in the case of simulating manufacturing performance.

The measurability of delivery performance in a manufacturing simulation model will be highlighted in this analysis by going through the list of delivery PMs provided by Beamon (1999) in section 3.2.2. The first measures revolve around on-time deliveries. Clearly, when excluding the distribution processes from the model, it is not possible to measure on-time deliveries in a meaningful way. A more relevant measure is rather shipped on-time (SOT), defined as an order ready for shipment from the FGW in full quantity, on-time. Modifying the PMs suggested by Beamon (1999) for on-time deliveries, the PMs related to SOT could be:

1) *Order lateness.* Shipment date minus shipment due date.
2) *Average lateness of orders.* Aggregate lateness divided by the number of orders.
3) *Average earliness of orders.* Aggregate earliness divided by the number of orders.
4) *Percent on-time shipments.* Percent of orders shipped on or before the shipment due date.

SOT could be considered as the manufacturing performance prerequisite for on-time deliveries. However, it is important to underline that the external customer factor is excluded, i.e. the delivery to the customer. Another consideration is to how orders are simulated. It is common, and arguably easier, to directly simulate shipments; i.e. using a distribution or a given schedule of shipments, orders are "shipped" from the FGW in the model directly when placed. Hence, in such models, the shipment due date is equal to the order placement date, and backorders occur instantly when the full quantity of an order is not present in the FGW. When this is the case, on-time delivery is not meaningful to measure.

Moreover, how the model is designed and hence what is measurable is largely dependent on whether the manufacturing system operates with a make-to-order or a make-to-stock strategy. SOT is for instance arguably more relevant for a make-to-order strategy. At the same time, a make-to-order strategy more or less implies that orders are explicitly modelled for the simulation model to accurately depict the real system. SOT is on the other hand not as important as master plan adherence (MPA) for a make-to-stock strategy, why explicitly modelling orders might not be important.

Regarding the measures for fill rate, backorder/stockout, and manufacturing lead time, they are all applicable in a simulation model of the manufacturing system, and can be measured as in the real system. Measuring customer response time needs to be modified similarly to on-time deliveries; instead of measuring the time between an order is placed until its delivery, it is only possible to regard time between an order is placed until it is shipped. The last two PMs suggested by Beamon (1999), i.e. shipping errors and customer complaints, are however not possible to capture in a simulation model of the manufacturing system. The former due to the lack of inclusion of the distribution in the model, and the latter for the same reasons as with measuring product quality; it is neither possible to capture customer responses in a meaningful way in a DES model.

Flexibility performance

Flexibility performance is arguably the most ambiguous and multi-faceted dimension of the manufacturing performance. Not only does flexibility itself disintegrate into multiple subdimensions, it can not be measured in terms of actual performance but only as potential performance (Beamon, 1999). As a result, flexibility can only be observed when reacting to uncertain events. Based on these properties, simulation is indisputably an excellent tool to evaluate the flexibility performance of a manufacturing system: By simulating what-if scenarios of uncertain events, such as machine break-downs, demand peaks, delayed raw material deliveries, etc., it is possible to observe what happens *if* one of these events would occur without doing costly tests on the real system.

However, not all dimensions of flexibility are equally easily measured using a simulation model. Those dimensions that only need to consider changes to the flow such as volume, delivery, rerouting, material and sequencing flexibility are generally easier to measure than product mix, change-over, and modification flexibility, which might require consideration on changes to the structure of the system[3] (Pehrsson, 2017), (Marklund, 2017). For instance, when a new product is introduced, it might be sufficient to include an estimated increased changeover-time and scrap-rate, but it may also be necessary to buy a new machine. Then, the time of e.g. delivery, installation, and training of staff needs to be considered. This can be

[3] See table 3) on page 47 for descriptions of the flexibility dimensions.

done either by including it generically into the model, reacting to some stochastic process which replaces a machine occasionally when a new product is introduced, or by modelling the specific event. To measure these dimensions of flexibility will thus potentially require either a more complex model or the specific modelling of the structural changes. Furthermore, these structural changes will have to be based on assumptions of their time consumption, which might negatively affect the accuracy of the measures.

While it is possible to simulate all kinds of uncertain events, it is hard to actually measure how the system performs in terms of flexibility (Gunasekaran & Kobu, 2007) Wiklund (2017). Without relating it to other performance dimensions, flexibility itself is a qualitative measure, describing how well the system handles the uncertainties. In fact, flexibility describes the level of deviation from the usual operational performance caused by the uncertainties. Not only is the simulation output from DES quantitative, but to assess this deviation, the flexibility performance dimensions need to be translated into quantitative measures to observe it. The collective view from theory and the external view is that the translation is done by studying the effect on other PMs, such as time, cost and delivery performance. Hence, the flexibility dimensions can be measured e.g. as the time it takes to return to normal inventory levels, the change in on-time deliveries, or the added cost due to overtime hours.

There are however multiple more ways to measure the flexibility dimensions. Beamon (1999) presents four formulas on how to measure volume, delivery, product mix, and new product flexibility (see section 3.2.2 on Flexibility performance). These formulas are of course only a selection of all existing formulas for measuring different flexibility dimensions. However, as examples and a basis for discussion, the continuing part on flexibility performance will discuss the applicability of the formulas on a simulation model.

Volume flexibility

The formula for volume flexibility measures the "long-run proportion of demand that can [profitably] be met" (Beamon, 1999, p. 286). As such, the volume flexibility is measured in percentage rather than a physical unit such as time, amount or cost. It further defines the volume flexibility as dynamic, depending the relation between capacity and demand [4]. Moreover, it is important to note that there is an emphasis on long-run proportion, i.e. it implies the relevance of volume flexibility

[4]Notably, if the simulation model excludes the demand and only studies the manufacturing output, then this formula is not usable.

on strategic decisions.

Regarding the PMs applicability in a DSS, the formula requires two input parameters:

1) D: the demand during T periods, either as:
    i) d_t: the demand during period t, for T number of periods; or
    ii) the distribution of D; and
2) $O_{\min}$ and $O_{\max}$: the minimum and maximum profitable output volume during any period.

If the demand is integrated in the simulation, then this input is already available for the user. Regarding $O_{\min}$ and $O_{\max}$, depending on the complexity of the manufacturing system, these parameters can be difficult to estimate without the use of a simulation. However, if the simulation model is connected with a cost model, these parameters can with relative ease be estimated by simulating different volumes and comparing the total cost with sales.

Delivery flexibility

The formula for delivery flexibility measures "the ability to move planned delivery dates forward" (Beamon, 1999, p. 288) as the percentage of slack time of which the delivery time can be reduced. The formula can be advantageously used in DSSS to evaluate the flexibility of production plans. By knowing the delivery flexibility of a plan and a system, it is possible to know what service level is reasonable to agree on with the customers.

Product mix flexibility

Beamon (1999) divided product mix flexibility into product mix flexibility range and product mix flexibility response. The former is a measure of "the number of different product types that can be produced within a time period" (p. 289). This measure is somewhat crude and does not take into consideration the volume of each products produced and the profitability. However, using estimations of the minimum profitable output volume ($O_{\min}$) from the the computation of volume flexibility, it is possible to use the simulation in order to compute how many different products can be produced without breaking the limit of minimum profitable output volume.

Regarding product mix flexibility response, i.e. "the time required to produce a new product mix" measured by "the changeover time required from product mix i to product mix j" (Beamon, 1999, p. 289), this can be measured in a simulation model as well. However, the authors argue that this computation is probably not benefited by the use of a simulation model.

New product flexibility

The formula for new product flexibility is again crude, defined as ”either the time or cost required to add new products to existing production operations” (Beamon, 1999, p. 289). As with product mix flexibility response, the authors question whether this is benefited by using simulation.

Chapter 6

Internal view

This chapter contains the viewpoints from the interviews of internal stakeholders in various positions and roles at Company X, together with observations from meetings and discussions. A description of the types of interviewees can be found in section 2.5.1 and for more details of the interviews, see appendix A, table A1. The interview material is presented in the form of three main topics and respective sub-topics. These correspond roughly to the structure of interviews, although it varied depending on the roles of the interviewees.

6.1 Observations from Pilot Project at Factory 1

The observations from the visit at Factory 1 and meetings with stakeholders both from the factory and the simulation project team, can be organised as follows:

1) Purpose and applications of simulation
2) Evaluating simulation results

6.1.1 Purpose and application of simulation

At Factory 1, there were three main application areas for the DSSS. Firstly, it would play a significant role in *planning decisions* through providing the ability to on a continuous basis test different production plans based on a master plan stretching over several months. This eventually would develop into a simulation-based optimisation tool rather than just a means of *experimentation.* There were also purely experimental purposes for the tool in two other main decision areas; *Layout design/Investments* and *Product mix.*

The need for a simulation- and optimisation-based tool proved to be multi-faceted. The main aspects were:

1) improve cost-efficiency and productivity (key business objectives)
2) improve the coordination between manufacturing, FGW operations and inventory management
3) simplify the task of planning production in the complex manufacturing system

Another important aspect, was the need to be able to respond to changing conditions, both in the business environment and from new strategic objectives from the central organisation. Questions were raised regarding how "fit" the factory would be to produce a certain product, in relation to other factories and in relation to the current strategic priorities. Also, the experimentation functionality could provide valuable decision support in case the manufacturing strategy for example were to shift from cost-efficiency to flexibility or vice versa.

6.1.2 Evaluating simulation results

One major aspect of the simulation project, and one of the major subjects of this thesis, was how the tool ultimately would be able to provide valuable, interpretable and credible decision support, rather than crude simulation output data. There was consensus among the project stakeholders that this would be more strongly emphasised in this simulation project compared to previous ones, to ensure usefulness of the tool. In addition, it became evident that in order to couple the simulation model (referred to as the *simulator*) with an optimisation algorithm (referred to as the *optimiser*), there would need to be embedded in the model, a performance evaluation to optimise against.

The stakeholders were generally open-minded about what could be appropriate performance measures, but their experience from previous simulation projects had been that simulation results can be:

1) difficult to interpret,
2) difficult to trust,
3) difficult to compare
4) mutually contradicting, and
5) difficult to act upon.

Their intuition was that one part of the solution was to include financial PMs, and potentially a "total cost" of a scenario. There was a particular focus on manufacturing costs and inventory costs. Their view was that this would make simulated alternatives easily interpretable for anyone and comparable "euros-to-euros". Furthermore, the long-term goal for the DSSS was to implement similar ones at other factories in the company's supply chain. Cost was argued to be a simple and universal benchmarking point between factories.

Another observation was that the tool was intended for use by a few, or perhaps one key stakeholder; the *superuser*. The primary stakeholder for the intended decision areas supported by the tool was the Planning Manager, who would receive training on the tool and become the superuser. He would through the tool receive decision support and/or optimised production plans for his own planning decisions and be provided with information on the planning decisions' joint implications on the factory floor, as well as on the FGW operations and inventory levels. Also, the tool itself should include some form of visualisation of the results, e.g. a *dashboard*, to make it a user-friendly decision support tool.

6.2 Manufacturing priorities and challenges

From a general company life cycle perspective, Company X is currently in a shift between a growth phase and a maturity phase (HQ: Proj. Engineer, 2017). The competition from external suppliers is also becoming stronger. This has several implications in relation to running the manufacturing operations. An earlier focus, which is evident particularly from the viewpoints of factory-based stakeholders, was building capacity for growing volumes. In many of the factories, this mindset of securing capacity to deliver is still outspoken, partly depending on their current demand situation. Now that the company is moving into the maturity phase, there is a growing interest for, and focus on, efficiency. There has traditionally also been a strong emphasis on costs, which according to the interviewees, both at the Headquarters and at the factories, persists. However, the cost focus is materialised in different ways at different factories, namely as either *resource efficiency* or *flow efficiency*, the latter a more recent priority. Quality was also mentioned as important by all the factory representatives, but mainly by referring to the *cost of poor quality* or scrap levels.

Along with the increasing interest for flow efficiency comes also *manufacturing flexibility*. On this matter there seemed to be somewhat diverging views. HQ: Proj. Engineer (2017) emphasised it as the way forward as the market conditions are changing. Also FAC3: Tech. Manager (2017) mentioned flexibility as a priority, as the particular factory faces smaller volumes and a greater product diversity to handle. FAC4: Prod. Planner (2017) was on the other hand ambivalent towards flexibility, claiming that their production is already fairly flexible and that increasing it would have negative impacts on the efficiency. His main concern instead regarded having enough capacity and productivity to meet the demand, while having several constraints and moving bottlenecks in the production.

All interviewees at the Headquarters and most factory representatives indicated a strong focus on bottom line results, at the factories. Meanwhile, HQ: BA, Ind. Strat. (2017) and HQ: Proj. Engineer (2017) both emphasised that some factories are somewhat lagging in the shift towards flow efficiency and flexibility. The former argued that historical growth has meant that some factories have been preoccupied with capacity and availability, sometimes leading to higher costs. When costs and efficiency had been on the agenda, Company X has sometimes seen competitors outperforming them, despite less resources and smaller volumes. HQ: Proj. Engineer (2017) highlighted that many of these factories had been growing in non-competitive, almost a monopoly-like markets, which he proposed as one likely explanation for this.

In contrast, HQ: Tech. Dev. Manager (2017) claimed that there is a fairly good alignment among the factories, and with the Headquarters, on the current manufacturing strategy, the priorities and the "way we work". He however pointed out that there might be some discrepancies as to where they are headed in a few years time. HQ: BA, Ind. Strat. (2017) also noted the efforts that had taken place to improve efficiency, mostly had been concerned with resource efficiency, including a strive towards maximising utilisation.

6.3 Performance measures and information-based decision-making

The internal view on performance measurement can be summarised as highly outcome-oriented. The decision-making can however not be described as measure-driven, especially not on tactical/operational levels in the organisation. Although it was typically mentioned a number of different measures used and reported on daily, monthly and yearly basis, most interviewees at the factories considered only one or a few of them as particularly relevant in their roles. In fact, many were not really concerned with performance measures and claimed to be relying more on principles, experience and knowledge about what works well and what does not, based on the current business situation of the factory.

It should furthermore be noted that many interviewees at the factories had difficulties in explicitly answering questions regarding the role of performance measurement in decision-making. Often, they merely referred to "information" or "aspects" of performance, which will also be evident in section 6.4 below.

6.3.1 Financial and non-financial performance measures

Among the interviewees, the views on financial and non-financial PMs, as well as the link and balance between them, were diverse. HQ: BA, Ind. Strat. (2017) emphasised that most decision-makers have a distinct financial mindset. He further suggested that there might be a high acceptance across the company for using financial PMs, as most decision-makers arguably are more experienced and accustomed with relating to financial numbers. He further noted that for a person working with Supply Chain Management, the level of focus on financial issues appears somewhat unusual. Moreover, HQ: BA, Ind. Strat. (2017) expressed a need for bridging the gap between those who understand finance, and those who understand logistics and production.

As evident from the simulation project at Factory 1, financial evaluations of simulated scenarios had been discussed extensively as a desirable information-base for decision-making. HQ: Proj. Engineer (2017) highlighted specifically the running cost. He also observed that collecting information needed to calculate these financial measures, such as the cost of inventory, is difficult today. In addition, as interest had grown for flexibility in the production, he sought means to evaluate and measure flexibility, as well as knowledge about how to increase it.

HQ: Tech. Dev. Manager (2017) acknowledged the existence of a financial mindset mentioned by HQ: BA, Ind. Strat. (2017), and further argued that applying financial on lower decision levels than the strategic, could be beneficial. His argument was two-folded. First, it would mean that decision-makers to a higher extent would be "speaking the same language". Second, he explained that it would be good for creating a sense of proportions, meaning that decision-makers would be able to relate financial magnitudes better. He exemplified with a hypothetical case in which a mid-level technical manager would refuse to purchase a new set of useful tools for technicians at the cost 5 euros, due to a tight maintenance budget. The decision might have been different if the financial impact of decreasing the machine downtime by 50 % through better tools had been evident. However, several interviewees believed that the link between operational- and financial measures is not very clear.

HQ: BA, Ind. Strat. (2017) reasoned that it perhaps would be difficult to draw anything more specific than a "dashed arrow" from an operational scorecard to a P&L-statement, but that such an arrow in fact could be desirable. He emphasised that the mere *understanding* of financial impacts from operational decisions, rather than any specific numbers, could improve decision-making significantly. He added that the accuracy of such numbers is likely to be low in a simulation model, and for credibility and acceptance purposes, one should probably choose measures that can be verified. Although, he suggested that some connections between operations and finance might be quite "hard-wired".

FAC3: Tech. Manager (2017) also had the opinion that there is no straight line from operations to finance, although some connection most certainly exists. He explained that the connection is dependent on the business situation; if capacity exceeds the demand, improved throughput or efficiency in the factory does not necessarily result in an improved financial bottom-line, even though such improvements may still be beneficial. However, he argued that Quality is in fact "hard-wired":

> *"[...] it's not a direct link between operational efficiency and financial performance. But if we're talking about quality, then it's direct money in the pocket."*

On the operational side, both HQ: BA, Ind. Strat. (2017) and HQ: Tech. Dev. Manager (2017) deemed Overall Equipment Effectiveness (OEE) an important and useful measure. One reason, they argued, is that it to a quite large degree is implemented, understood and followed in the factories. HQ: BA, Ind. Strat. (2017) believed it has a clear meaning, as most decision-makers in the factories can relate both to the measure itself, and its efficiency-based components.

However, he saw that as it had been used as an indicator of efficiency, the focus had sometimes been too narrow and not been *aggregated* on several machines. HQ: Tech. Dev. Manager (2017) saw potential in some form of aggregated OEE as a means of avoiding sub-optimisation. Most interviewees at the factories confirmed that OEE is either one of the Key Performance Indicators (KPIs) on the shop floor, or is about to be implemented as one.

In general, the main operational measures mentioned were mostly related to quantities (total, percentage or per time unit), availability, capacity, utilisation and quality(total scrap/rejects or percentage).

6.3.2 Information type and detail

All interviewees at the Headquarters argued that there were clear differences in the type, and particularly the *detail*, of information and PMs relevant for decision-making on different organisational levels. HQ: Proj. Engineer (2017) claimed that the actual PMs could in many cases in fact be quite aligned over the levels, but that the main difference would be their level of detail.

HQ: Tech. Dev. Manager (2017) explained that closer to the operational level, the decision-making is very much based on *current* information available. Decisions had to be made fast and be based on quick analyses, whereas on the strategic level, a decision's information-base could "tumble around" for some time before the decision was finally made.

HQ: BA, Ind. Strat. (2017) reasoned that information generated by simulation should probably be distributed similarly as in real operations, namely with measures such as planning accuracy, WIP, availability and alike. On the strategic level, he claimed that the measure structure typically resembles the Profit & Loss (P&L) statement, and he did not see any clear differences to the structure in the case of applying simulation.

FAC2: Tech. Engineer (2017) argued that although most measures probably would be the same in the case of using simulation, some of them could in fact be different when they had a simulation tool in front of them. He also argued that the detail and accuracy of the information-base for decisions related to the design of operations, is more important than those related to the size of the investment in design projects. He explained that the impact of "one million up or down" in the investment would eventually be dwarfed by one operator too much in continuous operation, calling for more measures and information on the operational level in the case of applying simulation.

FAC3: Tech. Manager (2017) claimed that they were using too many measures, implying that most of them were not central components in his decision-making. He listed a selection of measures from his monthly report amounting to over 30 performance measures (referred to as KPIs), categorised into Material, Operations, Supply Chain, etc. Some of them were further divided on factory-, line- and equipment level.

In relation to applying simulation, FAC3: Tech. Manager (2017) argued that the organisational level and function for which simulation would constitute decision-support, there would definitely be differences as to which information that would be relevant to which decision-makers. He argued that it would be interesting for him see the impacts of scenario over a longer period of time, whereas his subordinates for example in the planning department would rather be interested in which batches to plan in which order, for the upcoming week.

6.4 Simulation application areas

This section is organised according to the intended main areas of application for simulation at Company X, as identified by HQ: Proj. Engineer (2017) and the authors. These also correspond to the stated scope of the simulation project at (pilot) Factory 1, although most interviews were not conducted with stakeholders at Factory 1.

6.4.1 Production design and investments

Depending on the roles and experiences of the interviewees, they either had viewpoints on the role of a DSSS in different application areas or referred entirely to decision-making in their own responsibility areas.

Greenfield factory design projects and layout design in existing factories are the main areas in which simulation have been applied before. FAC2: Tech. Engineer (2017) has no experience with simulation, but has been involved in several such design projects before. He believed that, despite his limited knowledge of simulation, it has the potential to help him improve the accuracy of his analyses.

From the design perspective, he saw that perhaps the largest benefit of applying simulation in his role is to improve the understanding of moving bottlenecks by studying the system over time, as well as seeing the upper and lower limits on different variables. This would already in the design phase provide him with the information to modify and optimise the design to achieve the best conditions for high performance, while making sure that it would fulfil capacity requirements. Currently, he relies solely on his experience, simpler Excel-models and some paper calculations.

Apart from improved bottleneck analysis, he saw a potential to gain information on what the optimal batch sizes would be, which also would impact other design parameters such as the size and capacity of buffers or machines. The main principle of making design choices he described as "fit to production needs", meaning a logical production flow, short distances (minimum transportation), minimum labour, sufficiently little space consumed and sufficient production speed. He described that a design choice is typically based on an evaluation of whether it is "enough" for the expected volumes. He explained:

> *"When I design the buffers, then I always try to find the most critical item or most critical production case. From a volume point of view. I take the case with the biggest output, biggest volume, and design from that. Good or bad, this is how I do it. So I know that the size is enough."*

This issue was also related to whether the design would be feasible over time. FAC2: Tech. Engineer (2017) claimed he could rarely rely solely on some estimated *average* capacity requirement, as it depends on future volumes and may vary over time. Some form of "worst-case" analysis combined with common sense is therefore needed, he explained. Flexibility was also mentioned as something he considers in the design choice, referring to the robustness and ability to produce in critical situations, such as machine breakdowns.

FAC1: Planning Manager (2017), who does have experience from previous simulation projects, emphasised the benefit of using simulation in design cases or investments as being able to introduce variables in the analyses of production performance, not possible to study otherwise. More specifically, he mentioned the possibility to study buffer- and machine performance more in detail, including occupation, WIP-evolution, bottleneck analysis and line balancing.

FAC1: Fin. Manager (2017) also has experience from design projects where simulation studies has been part of the decision-support. The focus had mainly been on securing the ability to deliver a wide product range, therefore simulation had been used to study buffers, equipment and product mixes to dimension adequate capacity at minimum investment.

FAC3: Tech. Manager (2017) has no experience from simulation, but argued that simulation's potential role in investment decisions could be to gain more insight into whether an investment decision is good or bad, but perhaps even more to "know what he is investing in". He added that this would include evaluating the investment both on strategic- and on shop-floor level.

From the interviews at the Headquarters, a slightly more holistic view was presented. HQ: Tech. Dev. Manager (2017) argued that the by far most important aspect when stakeholders at factories evaluate investments, is payback time and costs. This partly has its explanation in a strong cost focus around the whole company, he believed. Although he saw a healthy degree of patience in longerterm investment results, there is sometimes a tendency of shortsightedness and focus on quick bottom line results.

Another observation he made was that in smaller investments or improvement initiatives, decisions are sometimes made quite ad hoc and that there is not always easy to isolate and evaluate the specific effects afterwards. In addition, he also saw a degree of sub-optimisation. He believed some units tend to adjust their parameters with focus on their own results, while that not necessarily is beneficial in a wider value chain perspective.

HQ: BA, Ind. Strat. (2017) also saw instances of sub-optimisation, such as looking to narrowly on maximising the performance on individual machines, leading to excessive buffers between them. In contrast, he exemplified that there are other factories producing boards, which have completely integrated production lines with virtually no buffers. For these factories, he stated that in a simulation project one would be forced to study everything and not specific parts in isolation. Otherwise, this kind of sub-optimisation occurs. Both HQ: BA, Ind. Strat. (2017) and HQ: Tech. Dev. Manager (2017) argued that one major benefit of using simulation is to capture the dynamics of, and build understanding in, interrelated manufacturing processes.

6.4.2 Planning and operations

All the stakeholders interviewed with responsibilities for production planning or daily operations had very limited experience from simulation, or none at all. They did however mention similar decision-making challenges in their roles, for which they saw benefits of improved decision-support. Especially FAC4: Prod. Planner (2017) emphasised the difficulty of dealing with the complex system and trying to meet high demand under a variety of constraints, in combination with unforeseen events.

In response to what made it so complicated to make a good plan, he stated:

> *"[There are] many different aspects and things that we actually don't have any control over. For example, suppliers' ability to deliver, [machine] breakdowns, etc. We can adjust the plan for some breakdowns, but when machine breaks down it's always happening in the worst possible moment. Sometimes you might be expecting it, but it is impossible to plan for."*

He added that it sometimes is often a question of deciding which constraints that are the most significant at the moment. Furthermore, it sometimes proves impossible to meet the demand and that the plans are often subjected to changes over time. The highest priority according to him is to meet the demand, but also to do so at the lowest possible cost.

FAC4: Prod. Planner (2017) further proposed that simulation could be of great help to him if it would allow him to easily compare whether a production plan and its volume, is feasible. He was also interested in better ways to compare and analyse the effects of changeovers between products.

FAC2: IT Specialist: Fin. Dept. (2017) explained that a high priority is to maximise the utilisation in the packaging department. He too noted that plans often change as time progresses, based on the current status of the production. (FAC1: Planning Manager, 2017) also found constraints and interrelated processes as challenging in production planning. He described the aim of the planning department as to level out production while meeting delivery to packaging department. They try to achieve this by incorporating the constraints already in the master plan.

FAC3: Prod. Planner (2017) mentioned that information on sequences and setups would aid him in the planning process. However, he noted that his priorities when making planning decisions are very dependent on the situation, for example whether the demand is high or low. When demand is high, the efficiency and capacity to deliver are important to consider. According to him, this would for example mean that large batches are desirable. But currently, as mentioned in section 6.2, the volumes in Factory 3 are often below capacity and demand diversity is growing. This makes them aim for smaller batches and more flexibility in the production.

In general, the planning stakeholders all described decision-making as a quite difficult task. This is in line with the experience of HQ: BA, Ind. Strat. (2017), who suggested that there could actually be even larger monetary benefits to gain by improving in this area of the operations, than for design projects and investments. FAC2: Tech. Engineer (2017) also pointed out that the investment is after all only made once, whereas poorly designed operations would build up significant costs over several years.

Related to this, FAC2: IT Specialist: Fin. Dept. (2017) also emphasised that the accuracy in information provided by the DSSS for planning purposes would need to be much higher (around ± 5%), than for analysing investments or strategic scenarios (where perhaps only ± 30% accuracy would suffice, or at least be as good as one could reasonably expect).

6.4.3 Product mix

Most of the interviewees with planning roles were unable to provide any clear opinion on how simulation could aid in evaluating whether a particular product should or could be produced in the factory or not. However, (FAC2: IT Specialist: Fin. Dept., 2017) viewed the issue of running "complicated" and "non-complicated" products in the same factory as problematic.

FAC4: Prod. Planner (2017) mentioned that one of the main restraints he considers in the planning process is to avoid too many colour changes in the lacquering department, as these changeovers are time-consuming. As described above, FAC3: Prod. Planner (2017) too emphasised the impact of changeovers on production efficiency and planning. FAC1: Planning Manager (2017) expressed that he sees as an important part of the implementation of a simulation tool at Factory 1, the possibility to get better understanding of the impact of changing the product mix. In fact, that is one of the main focus areas.

HQ: Tech. Dev. Manager (2017) described the process of assigning products to specific factories as a quite quick and intuitive process. He argued that there are not one or a few parameters that are studied, but rather an overall assessment, in which the factories' product cost calculations are one part. Other aspects considered are more based on the situation, such as which products that are to be phased out in the near future, the factories' current free capacity, their current product mixes and various supply risks associated.

HQ: BA, Ind. Strat. (2017) argued that one of his current priorities is to improve the possibility to benchmark between factories, partly to be able to make this type assessments more effectively and simulation could be one part of it. Previously, there had however been some resistance among some of the factories, possibly because it could decrease their autonomy and might affect the volumes for some of them negatively. He also saw historical explanations to why certain factories run certain products today, but argued that there could be benefits of more "specialisation" of the factories in the future. This could for example mean that high volume products are to be run in factories well adapted to such production and vice versa, instead of today's more ad hoc way of assigning products to factories.

6.5 Simulation as decision-support

As mentioned above and in section 2.5.1, many of the interviewees at Company X have little or no experience from simulation. In the interviews, most of them did however have opinions on decision-support in general and on what type of data or knowledge that is lacking today, or that could improve the decision-making. The expressed views were either related to some experience from simulation or a hypothetical case in which a simulation tool were to be developed.

Many interviewees expressed decision-making challenges in their roles that were similar in nature. To which extent they emphasised them, and in which functional terms they related to them, were the main differences. In total, four *decision issues* can be distinguished from the interviews. Table 8 below presents them, together with references to the interviewees who **most explicitly** expressed them.

Table 8. Identified decision-making issues and the respective stakeholders most explicitly supporting them in interviews.

	Identified issue	Stakeholder support
8.1	*Understanding process relations and constraints*	FAC3: Tech. Manager (2017) FAC1: Planning Manager (2017) FAC4: Prod. Planner (2017) FAC2: Tech. Engineer (2017) HQ: Tech. Dev. Manager (2017) HQ: BA, Ind. Strat. (2017)
8.2	*Dealing with variability*	FAC2: Tech. Engineer (2017) FAC3: Tech. Manager (2017) FAC1: Planning Manager (2017)
8.3	*Lack of holistic view or inclusiveness*	HQ: Proj. Engineer (2017) FAC1: Planning Manager (2017) HQ: BA, Ind. Strat. (2017) HQ: Tech. Dev. Manager (2017)
8.4	*Data versus information and knowledge*	HQ: Proj. Engineer (2017) FAC3: Tech. Manager (2017) FAC2: IT Specialist: Fin. Dept. (2017) FAC1: Planning Manager (2017)

In Table 8, Issue 8.1 was highlighted on different levels and from different organisational perspectives, namely by strategy, management, design, and planning stakeholders. Different factories and their respective operations, were different in terms of the level of complexity in the flow, from a process logic perspective. Factory 1 is for example more flow oriented than Factory 3, which according to FAC3: Tech. Manager (2017) is also significantly less spacious, has a more diverse product mix and no finished goods warehouse.

However, several factory representatives expressed similarly the difficulty of understanding how one part of the dynamic system is affected by changes to another, as well as predicting the effects of operational and planning decisions in general. Related to this, FAC3: Tech. Manager (2017) illustratively stated:

> *"You would have to be Nostradamus to predict what happens in this process."*

In particular, FAC4: Prod. Planner (2017) struggled with making sure capacity was not exceeded when making production plans, despite a number of different constraints in the system.

From a factory design perspective, concerns regarded mainly finding appropriate values on design parameters, such as buffer sizes, and how to handle moving bottlenecks (FAC2: Tech. Engineer, 2017). FAC1: Planning Manager (2017) argued that one of the main benefits of simulation is, by studying the whole system and its interconnected processes, to figure out the best overall flow, rather than looking at parts of the system in isolation. This view was supported by both HQ: Tech. Dev. Manager (2017) and HQ: BA, Ind. Strat. (2017). He also argued that one could see simulation as either to optimise within given constraints, or to evaluate/experiment with scenarios. The latter would involve removing or significantly altering constraints, although he saw no immediate or principal difference regarding how to use it.

Issue 8.2 was described by FAC3: Tech. Manager (2017), member of the management team at the argued more "customer-driven than planning-driven" Factory 3, as problematic when making decisions about a few years ahead. He noted that most predictions and forecasts are expressed with *averages*, while he in reality is more interested in the variations. Moreover, he argued that it would perhaps be more relevant for decision-makers to know what would happen when reality deviates from the plan; i.e. the consequences and the robustness of the system.

FAC2: Tech. Engineer (2017) emphasised as one of his main concerns in design factories and layout, the issue of seeing FAC1: Planning Manager (2017) further noted that what is most relevant is to see the *behaviour* of the system, rather than overall capacity and performance.

Mainly by interviewees at the Headquarters, and somewhat ambiguously, Issue 8.3 was described as one of the drivers for exploiting simulation. An earlier problem in simulation projects, had been a lack of knowledge about the aggregated effects on the system and in extension the overall benefit (bottom line result) of the initiative (HQ: Proj. Engineer, 2017), (FAC1: Planning Manager, 2017).

HQ: BA, Ind. Strat. (2017) argued that many initiatives had been too isolated, and sometimes the general view on performance in the factories as well. One effect has been a strong focus on improving the performance on machine level while overlooking the effects on the system as a whole. Some factories had for instance been trying to minimise setup times and maximise utilisation and efficiency on machines by running large production batches. What they had not considered sufficiently, was the effects on the finished goods stock and Work-in-process.

HQ: Tech. Dev. Manager (2017) proposed incorporating more simultaneous objectives into improvement efforts, such as for example improving the productivity while keeping WIP a reasonably low levels.

Finally, Issue 8.4 is related to a strong sense among most interviewees to keep things simple. Among stakeholders with experience from simulation, their view was that previous simulation projects had not provided outputs in the form of decision-support, but rather *data*. Even decision-makers with quite extensive knowledge and experience about operations management had been having a hard time evaluating whether to go forward with an initiative or not.

HQ: Proj. Engineer (2017) emphasised the importance of *interpretable* simulation outputs for decision-makers in different roles and with different level of knowledge. In addition, he argued that usable decision-support from simulation should provide the ability to easily compare the impact of a solution or scenario with something else.

FAC2: IT Specialist: Fin. Dept. (2017) was reluctant towards whether more information to support decision-making would make things easier. He did however see the value of DSSS in a more distilled format, possibly as *suggestions*. FAC3: Tech. Manager (2017) argued that they in fact have quite accurate and relevant information when making decisions. He nevertheless agreed that they could benefit from introducing more, or at least *other types*, of information generated by simulation. That is, if the model can be trusted and if there is a balance between using data and the experience/intuition of the decision-maker.

In general, most of the different stakeholder roles had different views on what would constitute relevant decision-support to them. However, some of them argued that a DSSS should provide similar and aligned information on production performance measures regardless of whether it was related to planning, layout design or other things. In addition, most interviewees believed that for decision-support, the information's level of detail would be higher for decisions of a more operational nature. Finally, several interviewees suggested that on the operational level, the *time perspective* was highly relevant. This refers to evaluating performance and behaviour over time.

Chapter 7

Empirical analysis

This section uses the theoretical view in combination with the conceptual analysis to further analyse the internal view on simulation as decision-support, decision-making and performance measurement in different decision areas. The aim is to answer the research questions and fulfil the purpose of the thesis, both in general and specifically for Company X.

7.1 Addressing the decision-making issues

As was mentioned in section 6.3, the interviewed stakeholders did not appear to be measurement or data-driven in their decision-making. Several of them stated explicitly their scepticism towards *more data* to facilitate their decision-making. Rather than interpreting this as an expression of a certain culture (the sample size would in any case be too small for such a claim), it indicates that they have previously experienced a gap in the knowledge-progression pyramid. This is further strengthened by observations from the project at Factory 1, namely that they had been having trouble interpreting and making decisions based on simulation results before.

There is therefore a need to bridge this gap, all while considering the specifically highlighted decision-making issues in table 8 on page 129. As was concluded in section 5.1.3, *Integration* and *Aggregation* are important considerations when attempting to use simulation as decision-support. This section therefore aims to find how they relate to the specific issues found at Company X, which will provide a basis for how they should measure performance in simulation-based decision-support.

7.1.1 Understanding process relations and constraints

The first observation that can be made around this issue is that it is related to the level of **vertical integration**. In order to understand and evaluate how connected processes affect each others' performance, one would need to include a sufficiently large share of them. It may also require an adequate level of **horizontal integration**, as processes may affect each other in different ways. In order to avoid too high complexity, some degree of simplifications will however be needed. It may be quite obvious what parts of the system that are unrelated, or least related, but it nevertheless has to be done carefully as some processes may affect each other more than expected. For the level of horizontal integration, a high number of different measures may be extracted without adding too much complexity, and the same logic of not disregarding too much applies. However, as Pehrsson (2017) noted, there are in reality not too many measures that are in fact relevant, and these should be aligned with the objectives of the decision-maker.

In terms of **information aggregation** and **time aggregation**, how to address this decision-making issue ought to be dependent on application area and decision-level. As shown in table 2 on page 42, the operational level typically requires more detailed information than the strategic. This view was further supported by several interviewees. However, FAC3: Tech. Manager (2017) who is a member of the management team at Factory 3, expressed concerns about too aggregated information in the form of averages. As mentioned in section 6.5, FAC1: Planning Manager (2017) was interested in seeing the behaviour of the simulated system even on a more strategic level, similar to what FAC2: Tech. Engineer (2017) expressed from a factory design perspective.

It can further be noted that many interviewees had constraints and bottlenecks as their main concerns, which according to Pehrsson (2017) is a very suitable area to apply simulation. Whether specific tools and features for sophisticated bottleneck analysis are built into the DSSS or not, it therefore seems that its level of integration and aggregation should not obstruct such knowledge from being created. Thus, the level of integration should be high enough to include all potential bottlenecks and the level of aggregation should be low enough to reveal them. In line with section 5.1.2, a major benefit to reap from simulation is learning and understanding the dynamics of the real processes.

Conclusively, to address this issue it is important to capture an adequately large part of the system and its performance, through integration. What is a suitable level of aggregation seems to depend on the decision-level and decision-areas simulated. For operational decisions, much suggests that high aggregation may be inappropriate due to the bluntness of the knowledge produced. Even for higher-level decisions, it also seems that too high a level of aggregation might be obstructive for some decision-makers.

7.1.2 Dealing with variability

This decision-making issue is most evidently related to the level of *time aggregation*. As previously mentioned in 7.1.1 above, several interviewees were interested in variation and dynamics. FAC3: Tech. Manager (2017) was mainly interested in the implications of *deviations* from the expected. FAC2: Tech. Engineer (2017) felt a need for better knowledge about what actual minimum capacity would be needed over time, rather than designing the buffers, machines etc, based on averages. By the time of the interview, he instead usually based the design on the worst case. This mindset was not only evident in relation to factory design cases, but also in planning and operations. Many interviewees showed a tendency to "safeguard" against variability and uncertainty through conscious yet deliberate over-sizing or overestimation. This could be connected to historical growth and a strong focus on *capacity to deliver* discussed in section 6.2.

Analogous to what was discussed in section 7.1.1 above, in order to better reveal the dynamics and to better balance capacity, the levels of integration and aggregation should be carefully set. Too low a level of integration may fail to capture important dynamics. Too high a level of information or time aggregation may conceal the true causes of issues and bottlenecks, or the cases in which they occur, preventing them from being properly resolved. In a design situation, this may cause a treatment of symptoms through even more over-sizing of e.g. buffer space, or unnecessarily expensive equipment, or poorly balanced production in general. In planning and operations, it could cause excess inventory/WIP, activity slack time or poorly balanced capacity.

7.1.3 Lack of holistic view or inclusiveness

Looking too narrowly or disregarding relevant parameters and parts of the manufacturing system was highlighted mainly from the interviewees at the Headquarters as evident in previous improvement efforts. This is inherently a strategic concern and can be referred to as nearsightedness, namely in terms of process myopia and performance myopia. Process myopia would mean for example disregarding the FGW when "optimising" production efficiency (e.g. through large batches). Performance myopia would mean focusing too much on individual aspects of performance, such as investing in a machine with high production speed while failing to consider its flexibility (e.g. the changeover time).

The link between these two concepts and **integration** is somewhat evident. In order for decision-making in design cases and improvement efforts to be more holistic and inclusive, so must a DSSS tool supporting such decisions. Thus, to mitigate process myopia the level of vertical integration must be sufficiently high. To avoid performance myopia, the level of horizontal integration should be high enough.

Regarding the level of aggregation, a reasonable claim is that a fairly high degree of information aggregation is needed for the decision-maker to actually evaluate whether an improvement or design choice is beneficial for the system as a whole. As mentioned in section 6.5, this explicitly argued to be one of the main drivers for implementing simulation-based decision-support.

7.1.4 Data versus Information and Knowledge

As was mentioned in the introduction to this section, this issue is related to bridging the gap in the knowledge progression pyramid (see figure 4 on page 37 and figure 13 on page 95).

It seems apparent that aggregation is a means of condensing crude data and information from a simulation model, through a DSSS tool, to make it more interpretable and relevant for the decision-maker, as concluded in section 5.1.3. However, analoguos to what was discussed above in section 7.1.1, this decision-making issue was not specifically related to a decision or simulation application area. Thus, the level of aggregation is likely to be different in different application and decision areas, as well as on different decision levels. In certain cases, such as bottleneck analysis, too high aggregation may in contrast to information overload instead create an information deficit. It should also be pointed out that progressed knowledge does not necessarily have to mean fewer and more inclusive measures of performance, it can mean a better understanding of the processes simulated.

7.1.5 Appropriate levels of integration and aggregation

As evident from the discussion above, what would be appropriate levels of integration and aggregation not only depends on the targeted decision area. It could also depend on the most prevalent of the decision-making issues or challenges at hand. Using the developed Aggregation-Integration Matrix (AIM) in figure 15 on page 102, the decision-making issues identified at Company X can be related to the appropriate levels of integration and aggregation suggested in the analysis above. The issues are enumerated in accordance with table 8 on page 129, i.e.;

1) Understanding process relations and constraints
2) Dealing with variability
3) Lack of holistic view or inclusiveness
4) Data versus Information and Knowledge

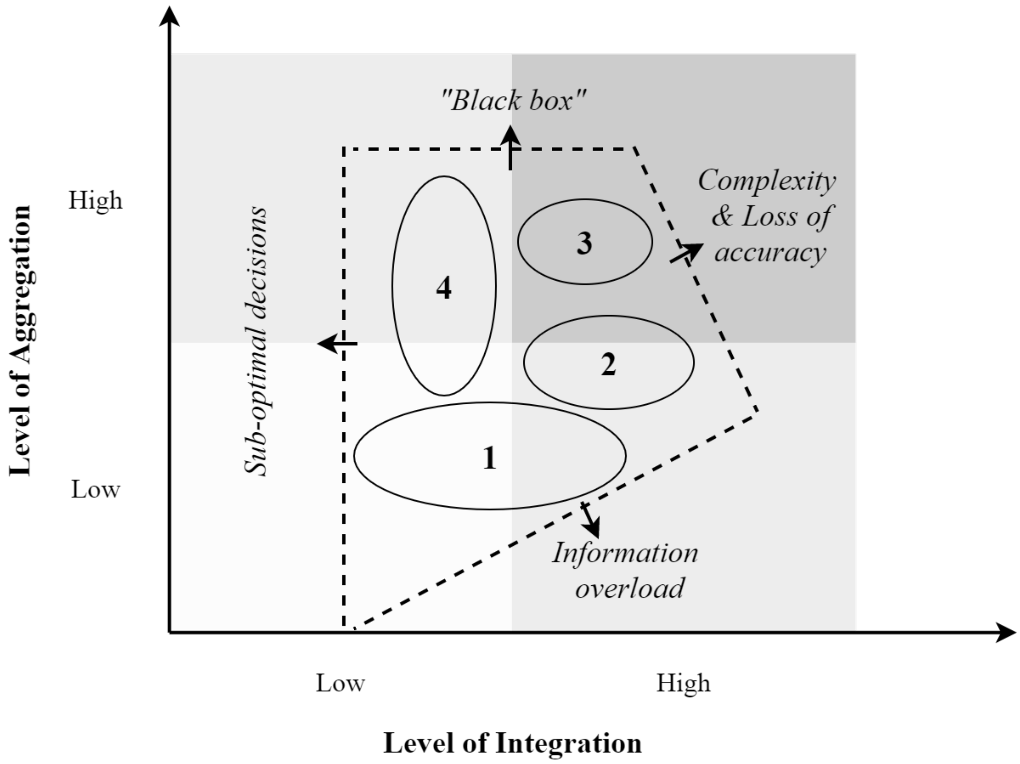

Figure 16. Suggested levels of integration and aggregation on the identified decision-making issues at Company X, using the Aggregation-Integration Matrix (AIM).

7.2 Designing a PMS for a DSSS at Company X

This section covers an analysis and discussion of how PMSs should be designed for DSSSs at Company X. It start with a discussion on how Company X's manufacturing competitive priorities should relate to design, and continues with a suggested approach on how to mitigate aggregation trade-offs.

7.2.1 Priorities and Performance dimensions

It was evident in the interviews that cost is an important consideration in almost all the decisions made. Most of the interviewees discussed the interview topics at least partly from a financial point of view, even issues on a quite detailed operational level. This indicates a cost-conscious and financial mindset, as was pointed out by HQ: BA, Ind. Strat. (2017) and others at the Headquarters, and which is also explicitly mentioned in Company X's own description of "culture and values". The cost-conscious and financial mindset is likely also what has led to the focus on *resource efficiency*; expensive equipment and personnel simply need to be utilised at maximum capacity. Consequently, when capacity utilisation has been high and ability to deliver a strong priority, it is not surprising that many investments and improvement efforts have revolved around how to produce more at the lowest possible cost.

Company X is moving into the maturity phase with increasing competition and eventually more stable volumes, as well as higher product diversity. As they do, focus seems to have shifted, at least strategically, more towards *flow efficiency* and *flexibility*. On this basis, there may be a need to complement the financial mindset with more elaborate methods and principles in pure Supply Chain Management. As HQ: BA, Ind. Strat. (2017) suggested, the financial and the operational side should try to meet in the middle.

Much evidence suggests that managing a manufacturing system, or an entire supply chain predominantly from a financial perspective, is problematic. The benefits of the financial measures themselves are however evident, both from theory, the internal stakeholders and the external view. Therefore, a combination of financial and non-financial PMs appears the most suitable for simulation-based decision-support at Company X. The appropriate balance between them is most likely dependent on the application area, as shown by the theoretical framework in figure 11 on page 74.

However, given the financial mindset at Company X and the need to bridge the financial-operational gap mentioned by HQ: BA, Ind. Strat. (2017), a slight drift of the appropriateness of financial measures may be needed. In other words, some financial measures may be relevant on lower levels in this case, than they would be otherwise. This could for example mean that simulation outputs in the form of labour hours consumed, average inventory level or alike, are translated into their respective financial value.

Flow efficiency tends to be measured in units of *time* (such as cycle time or cead time) or *percent* (such as aggregated OEE or percentage of Non-value added time) and not financially, although it certainly has *implicit* financial impacts. Improving flow efficiency revolves largely around finding specific instances and sources of long waiting time, bottlenecks and high WIP, which means that the knowledge provided by the DSSS needs to be quite specific and detailed. Meanwhile, as HQ: BA, Ind. Strat. (2017) remarked and which is much in line with theory, the idea of flow efficiency is to look at the system in a broader perspective, i.e. with higher degree of integration. Flow efficiency is integrated in itself, which also means that it would need to be considered on multiple decision levels, decision areas and on different time horizons.

Flexibility, as was described in section 5.2.3 under Flexibility performance, is multifaceted and reflects potential rather than actual performance. Some of the dimensions of flexibility can be calculated respectively using the models by Beamon (1999). However, as they are defined by different units of measure (cost, time, percent, units etc), there is no apparent way to aggregate multiple dimensions into one single measure of flexibility. Given the expressed aim of improving flexibility at Company X, it seems reasonable that at least one or a few flexibility measures, for example of those proposed by Beamon (1999), should be included in a DSSS or simulation model.

Summary

The primary strategic considerations identified in the interviews can be summarised as:

1) Cost efficiency: Strategic focus and modus operandi at Company X
2) Flexibility: New market situation, uncertain future and higher product diversity
3) Flow efficiency: Reduce sub-optimisation and safeguarding

7.2.2 Measurement breakdown structure

Given the financial mindset at Company X, it may be possible to mitigate some of the bluntness and "black-box" issues of aggregated financial performance measures, by simply using them in parallel with their respective financial- and non-financial components. This can even create synergies between the benefits of low and high aggregation respectively. In accordance with the suggestion by HQ: BA, Ind. Strat. (2017), this is a way of creating the "dashed arrow" between detailed operational measures and their financial impact.

Building a PMS in the form of a breakdown structure is also much in line with the way the Performance Pyramid is built up (see figure 7 on page 45). Aggregated outcome PMs could for instance be used in conjunction corresponding predictive PMs. This would furthermore be in line with the design of the theoretical framework, in which operational applications of simulation/DSSS exclude higher-level measures but tactical/strategic do not exclude lower-level measures.

However, some issues remain. First, the accuracy of the aggregated measures is not improved by merely displaying its components. Second, the issue of ”information overload” not only remains, it might become even worse due to an even higher aggregation of measures and thus a higher volume of information. Moreover, an aggregation will in many cases consist of numerous assumptions (e.g. when aggregating inventory levels into total inventory cost, there would need to be assumptions regarding stock-out cost, holding cost rate, lost sales etc (Wiklund, 2017)). If the aim is to display all the information about how the aggregated measure is built, these assumptions might also need to be displayed, increasing the volume of information further.

7.3 Selection of performance measures

This section first discusses the findings from the empirical view, specifically focusing on the general relation between application areas identified and measures to choose. Thereafter, a simplified cost model to use in simulation is proposed by the authors. Lastly, the three application areas are discussed more in detail, and one PMS is suggested for each of them.

7.3.1 Applications and measures

The specified areas of application for simulation/DSSS at Factory 1’s pilot project are Design & Investments, Product Mix and Planning & Operations. These can be related both to the Performance Pyramid in figure 7 on page 45, and the theoretical framework in figure 11 on page 74. In the former, one important note is that the three application areas mainly consider the *internal effectiveness*, i.e. the right side of the pyramid. The exception may however be that deliverability to some extent can be captured by a DSSS. In the theoretical framework, the three application areas can be mapped somewhat accurately to the *strategic*, *tactical* and *operational* decision-levels.

Design & Investments are strategic, structural decisions, concerning *resources* and may be irreversible for a long time period. Product mix decisions are infrastructural decisions and may have a fairly long time horizon but are more easily reversed within a reasonable time frame. Planning & Operations concerns the left part of the figure, i.e. non- or infrastructural decisions on a tactical/operational level. These decisions fall within the categories *manufacturing policies* and *execution*.

As AlDurgham & Barghash (2008) note, most of the application areas of simulation in manufacturing are interrelated, meaning that it is not possible to separate them entirely from each other. It should be noted that product mix is merely a sample of *management provisions*. Altering the product mix could also induce resource decisions (e.g. the decision to expand the product mix may require investing in new machines or altering the layout). The authors have for the sake of simplicity categorised it into *management provisions*. Likewise, when simulation is applied for decision-support regarding resources, such as in factory design decisions, what product mix to run may well be an important aspect to include. Another important note is that a DSSS as defined by Tolk et al. (2009), regards a decision-support tool based on a simulation model representing an actual and existing manufacturing system. Thus, greenfield factory design decisions should not be seen as applications of DSSS, but rather as individual simulation projects since the simulation model to build a DSSS upon would need to be built from scratch.

7.3.2 A simplified simulation cost model

In this section an example of crude cost model is presented that is built on TDABC. The example is supposed to offer an intuition on how a simple model could be constructed that would generate an estimation of costs that is in the ballpark for Company X.

The demonstration is made using one product (X), which passes through the manufacturing system in following processes:

1) Raw material inventory
2) Process A
3) Buffer
4) Process B
5) FGW

Note that in reality, process A might be several consecutive processes. If the processes are similar in their characteristics or highly integrated, it is possible to observe them as one. In the following part of subsection 7.3.2, an example is provided of how the manufacturing cost and inventory costs for the system above could be modelled together with a simulation model.

Manufacturing cost

The premises of this is translating costs to hourly rates as briefly described in section 3.3.6. An example of this would be to compute a time equation for the cost/time rate (PCR_i) of a specific process (i):

$$PCR_i = \frac{C_i^{tot}}{CAP_i^{tot}} + \mathbb{1}_{\text{night}} * CR_i^{\text{night}}, \tag{7.1}$$

where

- C_i^{tot} cost of all resources supplied to process i during a time period t, e.g. labour, maintenance, electricity, and depreciation costs;
- CAP_i^{tot} is the total available hours of process i during the time period t, e.g. all shift hours.
- CR_i^{night} is an extra penalty hourly cost rate for extra costs inflicted by night shifts, e.g. marginal labour cost.
- $\mathbb{1}_{\text{night}}$ is an indicator function that is equal to 1 during night shift, 0 otherwise.

Then, the partial manufacturing cost for one unit after process A is:

$$MFC_X^{partial} = PCR_A T_A, \tag{7.2}$$

and the partial component value of product X after process A is:

$$\begin{aligned} V_X^{partial} &= RM_X + MFC_X^{partial} \\ &= RM_X + PCR_A T_A. \end{aligned} \tag{7.3}$$

The total manufacturing cost for one unit after process B is:

$$\begin{aligned} MFC_X^{tot} &= MFC_X^{partial} + PCR_B T_B \\ &= PCR_A T_A + PCR_B T_B, \end{aligned} \tag{7.4}$$

and the finished product X value is:

$$\begin{aligned} V_X &= V_X^{partial} + PCR_B T_B \\ &= RM_X + MFC_X^{tot} \\ &= RM_X + PCR_A T_A + PCR_B T_B. \end{aligned} \tag{7.5}$$

Where:

- CR_A is the hourly cost rate at process A;
- T_A is the time the raw material is processed in process A;
- RM_X is the raw material value for product X;
- CR_B is the hourly cost rate at process B;
- T_B is the time the partial component spends in process B;

Note that the process time T should be in the same time unit as the cost rate CR.

The time-logs from a simulation output can be used to determine T_A and T_B, by observing the time stamps when a component enters and exits the process. This time would effectively capture the time (and hence the cost) of rework as well. The extra cost of night shift would be captured by the time stamps indicating that the process was done during a specific time interval (e.g. 7pm to 6am) as defined in the indicator function. Cost of waste is furthermore just the component value after the process ($MFC_X^{partial}$ or MFC_X) when it enters the "waste bin" plus some potential cost for waste management.

Inventory cost

Now, consider the inventory costs for product X in this system.

The raw material, WIP, and FGW holding costs for the product X can be calculated as

$$IC_{RM}(T) = \sum_{t=1}^{T} \left| N_X^{RM}(t) - N_X^{RM}(t-1) \right| RM_X h_X^{RM} \tag{7.6}$$

$$IC_{WIP}(T) = \sum_{t=1}^{T} \left| N_X^{WIP}(t) - N_X^{WIP}(t-1) \right| V_X^{partial} h_X^{WIP} \tag{7.7}$$

$$IC_{FGW}(T) = \sum_{t=1}^{T} \left| N_X^{FGW}(t) - N_X^{FGW}(t-1) \right| V_X h_X^{FGW} \tag{7.8}$$

where,

- T is the number of time units observed, i.e. number of days, weeks, months or years
- $t \in \{0, \dots, T\}$ is a specific time unit observed, i.e. day, week, month or year
- $N_X(t)$ is the amount of product X in the corresponding inventory at time t.
- h_X is the holding cost rate for product X and its components for the observed time unit.

A measurement of $N_X(t)$ would be done at the beginning of each time period t, e.g. every 7th day morning at 7am. The shorter the total time observed time of the simulation, the more granular should the time unit be. If for instance two weeks are simulated, then the time unit should be days. It should further be noted that the holding cost rates are usually expressed as annual cost rates. If the observed time unit is not years, but e.g. days, weeks or months, then the holding cost rates have to be converted accordingly:

$$h^{monthly} = (1 + h^{annual})^{(1/12)} - 1)$$
$$h^{weekly} = (1 + h^{annual})^{(1/52)} - 1)$$
$$h^{daily} = (1 + h^{annual})^{(1/365)} - 1)$$

The holding cost rate should preferably be product/component group specific, reflecting their unique attributes such as size, sensitivity to deterioration, etc. In addition to the holding cost, a backorder penalty cost for the FGW is also advised. This cost should capture the penalty cost as described in the service-level agreement (SLA) and a potential additional cost for reputational damage. The backorder penalty should be activated when an order could not be shipped on-time in full, i.e. when an order is moved to a queue in the model.

7.3.3 Design & Investments

Objectives and performance dimensions

This application category can in essence be divided into three subcategories in accordance with those identified by AlDurgham & Barghash (2008), varying in scope;

1) Design system from scratch (i.e. greenfield/brownfield design)
2) Modify system on hand (i.e. re-design)
3) Improve system on hand

Initiatives within 2) and 3) are smaller in scope as they regard an existing factory and may be connected to a specific need or situation to resolve (such as increased volumes, worn-out equipment or new products). However, little in the interviews suggested that the overall objectives would be very different.

As Beamon (1999) has stated, it is important that the PMS reflects all the relevant aspects for the decision at hand. Including all relevant aspects is highly related to three of the identified decision-making issues:

1) understanding process relations and constraints
2) dealing with variability
3) lack of holistic view or inclusiveness

All of these are relevant concerns in design/re-design and improvement decisions. The mapping in figure 16 on page 137 suggests that adequately high integration is needed to solve them. It also appears intuitively correct that designing a new system, re-designing an existing one or improving its performance, requires considering many aspects. This essentially means that large parts of the theoretical framework in figure 11 on page 74 would need to be covered simultaneously.

Furthermore, in decisions of this sort, several stakeholders at Company X expressed a need to be able to compare different solutions or designs against each other, or at least against some *criteria*. This is somewhat related to the fourth identified decision-making issue, namely Data versus Information and Knowledge. For comparison, the results from a simulation model would need to be distilled to some extent, through aggregation.

Evaluating and finally deciding upon a system design or improvement based on a few aggregated measures might be effective. But designing the system from the start, or re-designing it if simulation results are not satisfactory, is likely to require more detailed information. A way of satisfying the universality criterion while maintaining enough details is to use a form of measurement breakdown structure as described in 7.2.2 above. On the other hand, that approach does not solve the all issues with aggregation/integration and might create new ones (e.g. information overload). It appears that it would be difficult to capture and display all the complexity with designing, re-designing or improving a system, in only a few aggregated measures by themselves.

The authors therefore suggest running simulation as decision-support in two phases, using different measures. The first phase primarily revolves around understanding the dynamics of the system, in order to design it in accordance with the operational objectives Flow efficiency and Flexibility. In the second phase, the design is evaluated financially using the simplified cost model described in section

7.3.2 and its long-term flexibility is evaluated. This appears to be necessary, in order to consider the three identified overall objectives in section 7.2.1 without creating increasing aggregation, integration, scope and the number of measures too much. The logic between the design phase and the evaluation phase is iterative. When a design solution is deemed well-functioning from an operational point of view, it is then scrutinised more strategically in the evaluation phase. If the solution is believed to be inappropriate, it returns to the design phase.

Measures

Table 9. Samples of performance measures for design and investment simulations at Company X

	Objective	PM	Unit	Structure	Tense
Design	High flow efficiency	Flow efficiency	%	Aggregated	Outcome
		WIP	Units/ Space/ Time	Buffer/ product breakdown	Predictive/ Outcome
		Lead time	Time	Product breakdown	Outcome
	Internal flexibility	Re-routing flexibility	Delta unit cost/lead time	Aggregated	Predictive
		Sequencing flexibility	Delta product unit cost/lead time	Aggregated	Predictive
Evaluation	Cost	Product unit cost	Euros	Product breakdown	Outcome
	External flexibility	Volume flexibility	%	Aggregated	Predictive
		Product mix/ changeover flexibility	Delta unit costs/ lead time/ flow efficiency	Product breakdown	Predictive

High flow efficiency

Flow efficiency can be measures both in absolute- and relative terms. In absolute terms, throughput time (or lead time) can be measured as the total time it takes for a product to go through the simulated system. This measure includes both the value-adding processing time in machines, and waiting time in buffers/inventory. A relative measure for the flow efficiency as the percentage of value-adding time can then be measured by calculating:

$$Flow\ efficiency\ (\%) = \frac{Average\ throughput\ time - Average\ time\ in\ buffer}{Average\ throughput\ time}$$

The throughput time should be considered an outcome measure, as it may be an objective in itself. The flow efficiency is on the other hand predictive of financial performance through for instance lower WIP and inventory. They are, however, aggregated both in time and in information, although they could be dis-aggregated on different products or product families/categories. The third measure is suggested in order to compensate for the bluntness of the other two. Since the Design phase corresponds to operational/tactic decision-levels, there is a need to understand the specific dynamics and causes of the results, namely the overall flow efficiency. The flow efficiency is strongly related to the amount of WIP in the system, which is why WIP is also displayed in order to create understanding of the relation.

Cost

The selected cost parameter is Unit cost, calculated using the simplified cost model described in section 7.3.2. The purpose of using the unit cost is to relate the quantity produced to the costs induced by a specific design case simulated. The unit cost will differ between different products, meaning that the measure should be dis-aggregated or displayed in a breakdown structure. Although a decision-maker might be interested in the "total" cost in a design scenario, the authors proclaim that this may not be meaningful in a design case without account for the total quantity which is produced in the simulation. If total cost is nevertheless desired, for example in a business case, it can simply be multiplied with the quantity produced. Strict attention should however be paid to the fact that it is based on a simplified model, and might become misleading if used explicitly in capital budgeting.

Internal flexibility

The internal flexibility should be considered in the Design phase, with the purpose of building it into the system from scratch. This might be less relevant if the design case is more of an improvement or a smaller modification of the system, rather than if it is a large greenfield project. It is however still important, since even single changes (such as replacing machine, modifying buffers etc) could impact the internal flexibility. Two measures are suggested; **Re-routing flexibility** and

Sequencing flexibility. These correspond to how well the designed system handles machine breakdowns and failed supplier deliveries respectively, as described by Beamon (1999) in section 3.

Both of these measures can be seen as inherent in the design, but could be measured implicitly by evaluating the impacts of machine breakdowns and failed supplier deliveries on other performance measures, *ceteris paribus*. The authors suggest that they are evaluated by measuring the relative, aggregated impact on Unit cost and Throughput time. This means that these measures would need two or more evaluated simulation scenarios, in order to be calculated. However, a simulation model is likely to be designed with account for machine breakdowns (such as in the pilot project at Factory 1) as well as failed supplier deliveries. This study does not focus on the design of simulation models, nor modelling of raw material warehouses, but these measures can and should be evaluated.

For re-routing flexibility, the approach could be to calculate the difference in unit cost and throughput time in one scenario excluding machine breakdowns, with one including them. Likewise for sequencing flexibility, the differences are calculated between a scenario with infinite supply of raw materials and one with occasional (stochastic) failed supplier deliveries. The results will be absolute or relative measures showing how sensitive the designed system is to these events, both of which were mentioned by factory stakeholders as problematic and difficult to foresee.

External flexibility

The external flexibility is the second consideration in the Evaluation phase, and can be seen as whether the seemingly well-performing solution appears robust towards long-term, external uncertainties. Two measures are selected; Volume flexibility and Product mix/Changeover flexibility. The first is relevant since it is meant to take into account that a design decision might be irreversible for a long time period and based on uncertain future volumes. Even if a design choice has been evaluated as beneficial in financial and operational terms, it might be sensitive to volume changes. Evaluating its volume flexibility may lead to better designs which are more robust over time. In addition, it allows for more informed decisions instead of the tendency identified at Company X to ”safeguard” against uncertainty.

Calculating volume flexibility can be done using the approach by Beamon (1999) in equation 3.3.

Product mix/Changeover flexibility can be separately evaluated using the same approach as described in section 7.3.5 below.

7.3.4 Planning & Operations

Objectives and performance dimensions

The PMS for Planning & Operations applications is designed with respect to the overall objectives in section 7.2. The specific suggestions and examples of performance measures in Planning & Operations is based on its more specific functional goal; producing and delivering the right quantity at the right time. This objective is well expressed in terms of delivery performance. The operational performance of a specific simulated production plan, can on one hand be described by whether it was possible to achieve. On the other hand, one also needs to measure whether shipment orders could be fulfilled and/or whether demand could be fulfilled.

Apart from the delivery performance achieved in the simulation, some level of flexibility is required. The chosen production plan and production setup should have some margin built in, since they tend to be changed over time. Furthermore, since the simulation model itself is based on various assumptions, the uncertainty of plans increases further and through that also the need to measure flexibility.

In addition to delivering the right quantities in the right times, it is important to do so efficiently. Particularly, the interviews at the Headquarters indicated that focus should be on flow efficiency, rather than resource efficiency.

The objective of producing and delivering the right quantity at the right time does not in itself necessarily require any financial measures or cost dimensions. But given that a DSSS includes the simplified cost model described in section 7.3.2, some crude cost measures can be calculated. Although the simplified model in itself is no predictor in itself, it allows for comparison between different planning- or operational decisions, and is a means of relating a certain level of operational performance to its impact on the financial side. This is a way of satisfying the specific wish at Company X to measure financial impacts of planning decisions.

Measures

The selected measures for DSSS applications in Planning & Operations is displayed in table 10 below.

Table 10. Samples of performance measures for Planning & Operations simulations at Company X

Objective	PM	Unit	Structure	Tense
Delivery performance	Plan adherence	%	Aggregated	Outcome
	Fill rate/Service level (FGW)	%	Disaggregated	Outcome
	Shipping on-time (SOT)	Amount/%	Disaggregated	Outcome
Flexibility	Delivery flexibility	%	Aggregated	Predictive
	Free capacity/ Utilisation	%	Aggregated	Predictive
High flow efficiency	Flow efficiency	%	Aggregated	Outcome
	WIP	Units/Space/Time	Breakdown	Predictive
	Lead time	Time	Product breakdown	Outcome
Cost	Unit costs	Euros	Product breakdown	Outcome
	Prime cost	Euros	Aggregated	Predictive
	Inventory cost	Euros	Aggregated	Predictive

Delivery performance

Three measures are selected in order to reflect delivery performance. Plan adherence is used to display how well the plan was fulfilled in the simulation. The goal is to measure whether the plan is suitable and feasible for the manufacturing system, and should be as close to 100 % as possible. Lower than 100 % indicates that the planned quantity was not met by the manufacturing system. The implication can be that either expensive overtime is needed to fulfil it, or that demand cannot be met. Above 100 % means overproduction, leading to excessive finished goods inventory. Consequently, plan adherence should be seen as an outcome-oriented measure. Furthermore, it is aggregated both in the information- and the time dimensions and defined as:

$$Plan\ adherence\ (\%) = \frac{Output\ quantity}{Planned\ quantity} \times 100$$

The plan adherence essentially deals with the question "Were the planned quantities produced, at the right times?"

The delivery performance of the simulated plan in relation to the demand can be reflected either by a service level measure (e.g. order fill rate), and shipments "on time, in full" (SOT). Fill rate as service level measure in the DSSS can be defined as:

$$SL\ (\%) = (1 - \frac{Backordered\ quantity}{Demanded\ quantity}) \times 100$$

This measure should also be considered as an outcome-oriented measure. It is aggregated in time to describe overall service level performance during the simulated time period, but could be dis-aggregated on different products or product families/categories to better reveal which products that are problematic. It aims a describing "Was the finished goods warehouse replenished with the right quantities, at the right times?"

Shipping on time (SOT) can in turn be defined in the DSSS as:

$$SOT\ (\%) = \frac{Orders\ fulfilled\ on\ time,\ in\ full}{Total\ number\ of\ orders} \times 100$$

SOT is also aggregated in time and indicates how large share of the orders that were filled and shipped no later than the due date. Plan adherence, Service level and SOT may be interchangeable or mutually exclusive depending on the preferences of the decision-maker, and may also depend on whether the factory runs primarily Make-To-Order or Make-To-Stock. Note also that both fill rate and SOT require a simulation model that keeps track of orders, and not just quantities.

Flexibility

Flexibility should in Planning & Operations be measured in two dimensions, one more elaborate than the other. Delivery flexibility can be measured according the quite elaborate formula by Beamon (1999), described in section in equation 3.4 on page 55. This type of flexibility represents the actual flexibility "status" of the system at any given moment, namely in terms of *slack time* or "average time margin". In extension, it answer the question "How much short-term safety time-margin did the system have on average?"

Having free capacity can be seen as another means of being flexible to sudden changes to the plan, although it is slightly less elaborate. It could however quite easily be measured by a simplified formula suggested by the authors, based on how far the bottleneck process on average was from maximum utilisation during the simulated period:

$$Free\ capacity\ (\%) = (1 - \max_{u_i}(u_1, u_2, \ldots, u_n)) \times 100,$$

where u_i is the average utilisation for the sequential process $i, i \in \{1, \ldots, n\}$.

High flow efficiency

Flow efficiency in Planning & Operations is suggested to be measured in the same way as in Design & Investments, using the same measures (see *High flow efficiency* in section 7.3.3 above).

Cost

Cost is included in Planning & Operations in order to create better understanding between operational- and financial performance. The Unit cost measure is suggested for creating the relation between the output volume and the induced cost, and can again be measured using the simplified cost model in section 7.3.2. However, to further increase understanding of the impact of planning decisions on cost, the authors suggest that aggregated prime cost and inventory cost should also be measured. In addition, it may mitigate the risk of "over-planning" in order to decrease the unit cost, as the total prime- and inventory costs will be affected negatively and the essential purpose or planning decisions is not to produce the maximum quantities, it is to produce the *right* quantities.

7.3.5 Product mix

Objectives and performance dimensions

Applying simulation/DSSS for the purpose of testing the impacts of different product mixes is somewhat different to the cases described in sections 7.3.3 and 7.3.4. First, the specific goals of doing so can vary significantly in different situations. Second, it is not tied to a specific function or organisational level. However, the objectives ought to be aligned with the strategic considerations in section 7.2; Cost efficiency, Flexibility and Flow efficiency. Essentially, the product mix "what-if" analyses using simulation can be seen as evaluations of the product mix- or changeover *flexibility* described by Beamon (1999), by means of evaluating the impacts on Cost efficiency and Flow efficiency. Therefore, the same measures as above can be used, and *should*, for the sake of consistency.

Measures

Table 11. Samples of performance measures for product mix simulations at Company X

Objective	**PM**	**Unit**	**Structure**	**Tense**
Cost	Unit cost	%	Product aggregated	Outcome
High flow efficiency	Flow efficiency	%	Aggregated	Outcome
	Lead time	Time	Product breakdown	Outcome

Chapter 8

Conclusions

In this final chapter, conclusions from the results and the following discussions is presented. First, a brief summary is presented of the research questions, the research process and the findings of the study. Following, the overall conclusions are presented, addressing how the key findings relates to the research purpose and how the research questions have been answered. Moreover, the contributions and implications of this study are commented. In the last section, recommendations on future research are discussed.

8.1 Overview of the Study

This section summarises the main parts of this study, in chronological order.

The first part of this study was the theoretical view in chapter 3, which examined the three main research topics within Manufacturing and their intersections:

1) Decision-making and support (section 3.1)
2) Performance measurement (section 3.2)
3) Discrete-event simulation (section 3.3)

With the literature as a foundation, chapter 3.4 presented a comprehensive theoretical framework in figure 11 (page 74) meant to aid the analysis of the external and internal views on the topics.

In chapter 4, the views of the external interviewees from the unstructured interviews were presented in a neutral, topic-based and narrative manner.

Chapter 5 constituted a conceptual analysis, analysing the theoretical view further and related it to the external view. In section 5.1.1, discrete-event simulation was related to the knowledge-based view on decision-making. Then in section 5.1.3 the concepts of *integration* and *aggregation* in simulation-based decision-support were introduced, together with a mapping matrix (AIM) relating them to each other.

Section 5.2 deals with the identified differences in performance measurement in the real world versus in a simulation model or DSSS, thus targeting RQ1.

Finally, section 5.2.3 discussed how the Manufacturing Performance Dimensions can be measured in simulation/DSSS models with the purpose of answering RQ2.

In chapter 6, the views of the internal interviewees from the semi-structured interviews were presented similar manner as the *external view*. The final part, section 6.5, extracted and distilled the general decision-making issues found, i.e. the issues that should be targeted by the simulation-based decision-support.

Finally, chapter 7 discussed the empirical findings, connecting them to the theoretical view and findings from the conceptual analysis with the aim of addressing **??**. Section 7.1 uses the Aggregation-Integration Matrix (AIM), developed in section 5.1.3, to address the decision-making issues found in 6.5. Section 7.2 outlines the relevant performance dimensions to capture, with respect to the situation of Company X, and suggested a performance measurement system divided into the three main application areas: Design & Investments, Planning & Operations, and Product Mix.

8.2 Findings

This section presents the findings of the study. First, the general findings related to the research topics are presented and discussed, followed by specific findings and discussions constituting the answers to the research questions

8.2.1 Addressing Research Question 1

To recapitulate, the first research question of this study was:

> What specific conditions does simulation-based decision-support put on the selection of performance measures and the design of a PMS, as opposed to performance measurement in a real system?

The following findings relate to using simulation as decision-support in general:

1) simulation can support decision-making in multiple different ways, through providing knowledge difficult or impractical to acquire otherwise
2) knowledge created by a simulation model/DSSS can aid decision-making in other ways than evaluating scenarios.
3) simulation and even a DSSS can only evaluate specific scenarios, it is up to the decision-maker to weigh and judge performance dimensions when they are subjected to trade-offs
4) the complexity of simulation is two-folded; it can capture the real system in a realistic way, but the outputs can cause confusion if not distilled properly in a PMS
5) The role of performance measurement in simulation-based decision-support can be described in terms of aggregation and integration
6) The level of aggregation and integration in simulation-based decision-support should be set carefully (see figure 15), to avoid:
   i) Sub-optimisation/Silo-thinking (too low integration)
   ii) Information overload (too low aggregation)
   iii) "Black box" problems/Lack of understanding and credibility (too high aggregation)
   iv) Complexity/Loss of accuracy (too high integration and aggregation)
7) Aggregation and integration should be aligned with the specific issues that the decision-maker faces, i.e. his/her specific needs in terms of detail and scope of the decision-support

Regarding simulation in itself, it is important to note that it is very useful to analyse and improve manufacturing systems, but it should be seen as support for the decision-maker, who naturally maintains a crucial role. Simulation-based decision-support should be aimed at improving the quality of decision-making, as well as simplifying the task itself, through addressing the issues that decision-makers face. If decision-makers struggle with understanding complexity and the long- and short-term impacts of decisions in the manufacturing system, then it is important to avoid making it *worse* by generating a vast amount of data or unstructured information. Instead, it is preferable if the tool can provide some parts of the analysis by itself and thus meet the decision-maker halfway. Integration and aggregation are two concepts which describe in what dimensions the simulation model/DSSS operates. Going too far in either direction can deteriorate its practical usability or *decrease* the quality of the decisions made, or both.

The following findings are built on those previously presented and apply specifically for designing a PMS for simulation/DSSS:

1) a PMS should, both in reality and in simulation-based decision-support, satisfy:
   i) Inclusiveness (sufficient integration)
   ii) Universality (sufficient aggregation)
   iii) Measurability (the captured performance dimensions should be possible to model and measure, meaningfully and accurately enough)
   iv) Consistency (aligned with organisational goals)
2) The inclusiveness and consistency criteria seem to require a mix of financial- and non-financial measures
3) Financial measures appear to be most relevant on higher decision-levels, but can be included in a simulation model/DSSS model
4) To calculate financial measures, a cost model needs to be constructed. Such cost models typically:
   i) require a significant amount of accurate, accessible and up-to-date input data
   ii) include numerous simplifications and assumptions, *in addition* to those already made in the simulation model

The simulation-specific criteria on the PMS used in a simulation-based decision-support application, can be expressed in the general properties of an effective PMS outlined by Beamon (1999). Appropriate levels of integration and aggregation are the means to satisfy inclusiveness and universality. Specifically, the inclusiveness criterion not only concerns what to measure, but also the scope of the underlying simulation model. Furthermore, the chosen levels of these should be addressing the specific decision-making issues faced by a certain decision-maker in a certain decision- and application area. The consistency criterion appears to apply analogously for PMSs in general and simulation modelling/DSSS specifically; the purpose and objectives are what ultimately defines what is relevant to measure.

Measurability is related to the specific benefits and modelling issues with simulation, which make some performance dimensions more easy to measure and others more difficult. This study has shown that there are differences to measuring a real system, as described in section 5.2. First, the *time factor* describes how the simulation model in a sense is capable of estimating future outcomes, given a certain set of input parameters and a valid simulation model. The implication on performance measurement is that the measure tense of some measures can essentially be seen as having shifted from "outcome" to "predictive", as the simulation model/DSSS tool in a some ways can be seen to *prognosticate* the outcome. For longer-period simulations, traditionally outcome-oriented measures may therefore have higher relevance, as the opposite would mean a evaluating a scenario of measures that are still only predictive. However, the predictive measures together can be important to capture performance dimensions not possible to include in the simulation.

The *resource factor* emphasises that the traditional measurement trade-off of benefit versus cost, can be seen to shift towards benefit versus modelling complexity. In other words, as the simulation model can measure what is modelled by the click of a button, the trade-off lies in building a model with a wide enough scope (integration) to measure what is of interest. In addition, several dimensions of performance can be particularly difficult (or impossible) to model and measure, such as product quality and customer satisfaction. Despite the differences of practical nature, what is relevant to measure is dependent on the manufacturing competitive priorities and objectives, as with performance measurement in manufacturing in general.

Conclusively, the general claim within the field of performance measurement that a mixture of predictive and outcome-oriented measures (and financial/non-financial) is preferable, appears to apply also in simulation. The most prominent difference in selecting performance measures in simulation versus in reality, appears to be what ultimately can be modelled and measured, with or without substantial effort.

8.2.2 Addressing Research Question 2

The second research question in this study was:

> What performance measures should be selected in a PMS in Simulation-based decision-support, depending on the areas of application?

This study finds that the selection of performance measures in a PMS for simulation-based decision-support should be aligned with:

1) the organisational goals and objectives in the simulated decision-area, and in extension the purpose of simulating
2) the decision-making issues and knowledge gaps for decision-makers in the simulated decision-area

The first conclusion is somewhat analogous to performance measurement in general, e.g. the structure of the Performance Pyramid in figure 7 on page 45. The second is more specific to the intended purpose of supporting the decision-maker and most likely relevant regardless of whether or not the decision-support tool is based on simulation.

As the PMS should be aligned with the purpose and objectives of using simulation/DSSS, three different PMSs were developed in tables 9, 10 and table 11. These correspond to the specific application areas identified by Company X: Design & Investments, Planning & Operations and Product Mix. They have some differences in content, but are all aligned with the identified strategic objectives (or manufacturing competitive priorities) identified at Company X:

1) Cost efficiency
2) Flexibility
3) Flow efficiency

Regarding knowledge gaps and in extension the specific needs of the decision-maker, four common decision-making issues has been identified at Company X:

1) Understanding process relations and constraints
2) Dealing with variability
3) Lack of holistic view or inclusiveness
4) Data versus Information and Knowledge

These were mapped into the Aggregation-Integration Matrix (AIM) developed in section 5.1.3, suggesting appropriate levels to solve them. They are not overlapping, which means that there may be no unique levels that can fully mitigate with all of them. In addition, they were not equally emphasised on different decision levels, meaning that a PMS should be separately displayed in different situations and on different decision levels.

Given the findings above, the suggested sets of performance measures found in tables 9, 10 and 11 are adapted to decision-levels and specific applications, address the identified decision-making issues and are aligned with the overall objectives identified. These constitute the response to RQ2 and are discussed further in the sections below.

Design & Investments

The authors suggest a two-phased approach for this application area, as seen in table 9. The reason for this was that Factory or Layout design changes, or improvement initiatives in general, may require to be evaluated both on an operational/detailed level and on a strategic/holistic level. Both of these views ought to be difficult to achieve in one single set of performance measures, given the conditions and criteria outlined in this study.

In addition, the two-phased approach with financial- and long-term flexibility evaluation can to some extent remedy the identified issue of ”safeguarding” in design choices, as the decisions would become more fact-based.

Planning & Operations

The flexibility dimension is included in this application area, even though it might be considered an inherent property of a manufacturing system, rather than something that can be affected substantially on the short-term. There are however, as shown, flexibility dimensions which do apply, also on the short-term.

One of the manufacturing objectives identified is improving flexibility, and it was also mentioned by several interviewees that unanticipated events are challenging within planning. Moreover, as simulation models are simplified and built on many assumptions, the need for evaluating the flexibility of a certain production plan increases further. Even if a DSSS tool provides information on the impacts of different production plans, albeit both financially and operationally, it almost certainly will not capture the true *probability* of such impacts. Or vice versa, the *risk* of reality to turn out differently, due to supplier delivery failures, operators on sick leave etc.

Product Mix

The product mix application area is, as discussed, not a functional application area in itself. The impacts of changes to the product mix at a certain factory will most certainly occur in many different parts of the manufacturing system. Therefore, the measures suggested should not be seen as static in any way, they are mere suggestions meant to serve as simple criteria. If the effects on cost measures or flow efficiency are not too high, a certain product mix can be seen as qualified for further study.

Again, the cost model suggested is highly simplified and does not provide information accurate or detailed enough to conduct product costing. Even if substantial effort was put into developing a more sophisticated model, it is far from certain that it would provide any better calculations than those used today.

It might be more effective for Company X to develop some criteria on which products to produce where, based on principles and factories with ”strategic profiles”. One such principle could be to produce ”simple”, high-runner products in certain factories focusing on that task, and more diverse product portfolios with volatility and low volume, in others. Assigning products to factories exclusively based on capacity and volume, may lead to short-termism and sub-optimality. This type of principle can be complemented with simulation, as a means to evaluate suitability of a product mix through the PMS suggested, but the overall assessment includes several considerations not covered by this study.

8.2.3 Concluding remarks

Since cost models can be difficult to achieve reasonable accuracy in, a simplified one was proposed in section 7.3.2. This model is proposed as a means of calculating the cost measures in the PMSs suggested. A simulation model is no predictor in itself, due to various assumptions and simplifications. Moreover, the cost model adds another layer of uncertainty in the decision-support. The cost measures themselves, should therefore be used mainly for "screening" and rough comparisons between scenarios, rather than predictions of financial performance.

Company X expressed that translating operational measures into financial impacts is attractive to better be able to evaluate whether to go forward with a simulation-based decision. It most certainly is, but one important conclusion to draw from this study is that performance in manufacturing is multi-faceted. Even if future financial performance may be the ultimate goal, it is in reality difficult to manage an organisation solely on the basis of financial performance. Some dimensions of performance are not possible to express in financial numbers, although decisions to improve them most certainly can have financial impacts, *implicitly*. First, the complete dynamics of financial impacts from operational performance improvements may be close to impossible to foresee. Second, some decisions may have significant long-term financial impacts which do not materialise during the simulated time-period, and which stem from factors not even included in the model. This is why Company X is advised to pay attention to the fact that the model is in fact a model, most evidently so regarding the cost measures. The authors however believe that the cost model, together with the other suggested measures together can provide a link between financial and operational performance. In the end, when building a business case for an investment or improvement partly based on simulation results, there will most often be more aspects to consider than financial measures and estimates.

According to the authors' experiences within the fields of Supply Chain Management, Logistics and Manufacturing, much revolves around trade-offs. If all sides of those trade-offs could be translated with moderate accuracy into financial numbers, they would be optimised and no longer constitute real trade-offs. Some trade-offs are *distinct* (such as batch sizes, setup costs and inventory) and may be optimised, others are more *diffuse* (such as efficiency versus flexibility). Many improvement methods in the latter, revolve largely around *principles* presumably leading to long-term performance. They typically focus on improved customer satisfaction, less waste of time and resources etc., rather than trying to predict the financial impacts of specific decisions, in specific situations.

8.3 Recommendations for Company X

Based on the findings above, together with the selected PMSs in the different application areas, some general recommendations can be formed for Company X.

1) Use a simplified cost model for screening solutions, rather than decision criteria
2) Adopt a TOC or *japanese lake* strategy, focusing on system constraints, when simulating for continuous improvement
3) Tailor Aggregation & Integration for the decision-making issues in the simulated decision-areas
4) Integrate all aspects that are possible constraining factors when building the simulation model
5) Align what to measure and model with strategy and purpose

The first recommendation recognises the benefits of using financial measures and costs, but also the complexity and difficulty of building a valid and accurate cost model. The benefits may be reaped without having to build a highly sophisticated cost model, which would be likely to have quite poor accuracy anyway. The second recommendation is related to the benefits highlighted by Pehrsson (2017), i.e. that using simulation to find and target bottlenecks is one of its main benefits. There also appears to be a synergy between such improvement methods and the use of simulation, as they can be automated and to a large part done virtually before implementing changes. The third recommendation emphasises that in order for the simulation-based decision-support to actually be of any use to the decision-maker, it should be addressing his/her actual decision-making issues and knowledge gaps. The fourth concerns the fact that too low integration can be an issue, namely by leading to sub-optimisation, disregard of important factors and/or failure to capture important dynamics in the system.

Finally, what to measure in the simulation is determined by what the tool actually models. In order to capture what is relevant for the decision-maker and for the organisation as a whole, the model and measures need to be grounded in what is intended to be achieved. Therefore, both the design of the model and the selection of what to measure should be aligned strategy and purpose, as well as lower-level objectives in the decision-areas simulated.

8.4 Contribution and implications for research

The main contribution to research of this study is a comprehensive conceptual and practical view on the role of performance measurement in manufacturing simulations and simulation-based decision-support. It presents the concepts of integration and aggregation and relates them to identified decision-making issues found at Company X, but can essentially be used in multiple different ways and in other settings. In addition, it applies previous research on performance measurement in the context of simulation, highlighting analogies, discrepancies and specific considerations which need to be paid attention to.

8.5 Recommendations for further study

This study could be followed by multiple different research projects. The first and most obvious suggestion is to study the implementation, and continuous use, of simulation-based decision-support in the application areas studied. This would provide more knowledge on practical issues and additional aspects targeting the usability. Also, research could be conducted focusing on making results visual in the most effective way.

Another key area which requires further study, is how to develop reasonably accurate cost models which are simple to develop and use, preferably with high degree of automation. Related to this, one particular area to study is whether it is possible to connect DSSS tools and cost models to financial, business intelligence and/or ERP systems. This could for instance provide updated and accurate financial data automatically, thus mitigating the common issues experienced before of acquiring input data.

Chapter 9

Bibliography

AlDurgham, M. M. & Barghash, M. A. (2008), 'A generalised framework for simulation-based decision support for manufacturing', *Production Planning & Control* **19**(5), 518–534.

Axelrod, R. & Cohen, M. (1999), *Harnessing Complexity: Organizational Implications of a Scientific Frontier*, Basic Books.

Banks, J. (1998), *Principles of Simulation*, John Wiley Sons, Inc and Co-published by Engineering Management Press, pp. 3–30.

Beamon, B. M. (1999), 'Measuring supply chain performance', *International Journal of Operations & Production Management* **19**(3), 275–292.

Bennet, A. & Bennet, D. (2008), *Handbook on Decision Support Systems 1, Basic Themes (International handbooks on information systems)*, Springer-Verlag Berlin Heidelberg, chapter 1, pp. 3–20.

Choudhari, S. C., Adil, G. K. & Ananthakumar, U. (2010), 'Congruence of manufacturing decision areas in a production system: a research framework', *International Journal of Production Research* **48**(20), 5963–5989.

Chryssolouris, G. (2006), *Manufacturing Systems: Theory and Practice*, 2 edn, (Springer Science-hBusiness Media, Inc.

Creswell, J. W. (2014), *Research design*, 4 edn, SAGE Publications, Inc.

Cross, K. F. & Lynch, R. L. (1992), 'For good measure', *CMA - the Management Accounting Magazine* **66**(3), 20–23.

Farahani, R. (2011), Logistics philosophies, *in* R. Farahani, S. Rezapour & L. Kardar, eds, 'Logistics Operations and Management', Elsevier, chapter 4, pp. 55–69.

Garvin, D. A. (1987), 'Competing on the eight dimensions of quality', *Harvard Business Review* **65**(6), 101–109.

Gunasekaran, A. & Kobu, B. (2007), 'Performance measures and metrics in logistics and supply chain management: a review of recent literature (19952004) for research and applications', *International Journal of Production Research* **45**(12), 2819–2840.

Gunasekaran, A., Patel, C. & McGaughey, R. E. (2004), 'A framework for supply chain performance measurement', *International Journal of Production Economics* **87**(3), 333–347.

Hayes, R. H. & Wheelwright, S. C. (1984), *Restoring our Competitive Edge: Competing Through Manufacturing*, John Wiley Sons, New York, NY, USA.

Holsapple, C. W. (2008), *Handbook on Decision Support Systems 1, Basic Themes (International handbooks on information systems)*, Springer-Verlag Berlin Heidelberg, chapter 2, pp. 21–50.

Hopp, W. J. & Spearman, M. L. (2008), *Factory Physics*, 3 edn, Waveland Press, Inc.

Jönsson, M., Andersson, C. & Ståhl, J.-E. (2008*a*), A general economic model for manufacturing cost simulation, *in* M. Mitsuishi, K. Ueda & F. Kimura, eds, 'Manufacturing Systems and Technologies for the New Frontier: The 41st CIRP Conference on Manufacturing Systems May 26-28, 2008, Tokyo, Japan', Springer London, London, UK, pp. 33–38.

Jönsson, M., Andersson, C. & Ståhl, J.-E. (2008*b*), Implementation of an economic model to simulate manufacturing costs, *in* M. Mitsuishi, K. Ueda & F. Kimura, eds, 'Manufacturing Systems and Technologies for the New Frontier: The 41st CIRP Conference on Manufacturing Systems May 26-28, 2008, Tokyo, Japan', Springer London, London, UK, pp. 39–44.

Kádár, B., Pfeiffer, A. & Monostori, L. (2004), Discrete event simulation for supporting production planning and scheduling decisions in digital factories, *in* 'Proceedings of the 37th CIRP International seminar on manufacturing systems', pp. 444–448.

Kaplan, R. S. & Anderson, S. R. (2007), *Time-Driven Activity-Based Costing: A Simpler and More Powerful Path to Higher Profits*, Applied social research methods series, Harvard Business School Press, Boston, MS, USA.

Kaplan, R. S. & Norton, D. P. (1992), 'The balanced scorecard: Measures that drive performance', *Harvard Business Review* **70**(1), 71–79.

Krishnamurthi, M., Jayashankar, R. & Philips, D. T. (1997), A generalized model cost analysis model for manufacturing simulation, *in* H. R. Parsaei, S. Kolli & T. R. Hanley, eds, 'Manufacturing Decision Support Systems', 1 edn, Chapman & Hall, London, UK, chapter 1, pp. 1–18.

Leong, G. K., Snyder, D. L. & Ward, P. T. (1990), 'Research in the process and content of manufacturing strategy', *International Journal of Management Science* **18**(2), 109–122.

Lockamy III, A. (1998), 'Quality-focused performance measurement systems: a normative model', *International Journal of Operations & Production Management* **18**(8), 740–766.

McGarvey, B. & Hannon, B. (2004), *Dynamic Modeling for Business Management*, 1 edn, Springer-Verlag New York.

Melnyk, S. A., Stewart, D. M. & Swink, M. (2004), 'Metrics and performance measurement in operations management: dealing with the metrics maze', *Journal Of Operations Management* **22**(3), 209–217.

Miltenburg, J. (1995), *Manufacturing Strategy - How to Formulate and Implement a Winning Plan*, 2 edn, Productivity Press, New York, NY, USA.

Modig, N. & Åhlström, P. (2012), *This is lean: Resolving the efficiency paradox*, Rheologica publishing.

Neely, A., Gregory, M. & Platts, K. (1995), 'Performance measurement system design: A literature review and research agenda', *International Journal of Operations & Production Management* **15**(4), 80–116.

Negabahn, A. & Smith, J. S. (2014), 'Simulation for manufacturing system design and operation: Literature review and analysis', *Journal of Manufacturing Systems* **33**(2), 241–261.

Netland, T. H. & Sanchez, E. (2014), 'Effects of a production improvement programme on global quality performance: The case of the volvo production system', *The TQM Journal* **26**(2), 188–201.

Ören, T. I. (2009), *Principles of Modeling and Simulation: A multidisciplinary approach*, John Wiley Sons, Inc., chapter 7, pp. 153–179.

Parker, C. (2000), 'Performance measurement', *Work Study* **49**(2), 63–66.

Pehrsson, L. (2013), Manufacturing Management and Decision Support using Simulation-based Multi-Objective Optimisation, PhD thesis, De Montfort University.

Pehrsson, L., Ng, A. H. & Benedixen, J. (2016), 'Automatic identification of constraints and improvement actions in production systems using multi-objective optimization and post-optimality analysis', *Journal of Manufacturing Systems* **39**, 24–37.

Pehrsson, L., Ng, A. H. & Stockton, D. (2013), 'Industrial cost modelling and multi-objective optimisation for decision support in production systems development', *Computers & Industrial Engineering* **66**(4), 1036–1048.

Pijpers, G. (2010), *Information Overload: A System for Better Managing Everyday Data*, John Wiley Sons, Hoboken, N.J., USA.

Reynolds Jr., P. F. (2009), *Principles of Modeling and Simulation: A multidisciplinary approach*, John Wiley Sons, Inc., chapter 2.

Robinsson, S. (2015), A tutorial on conceptual modeling or simulation, *in* L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal & M. D. Rossetti, eds, 'Proceedings of the 2015 Winter Simulation Conference', pp. 1820–1834.

Rudberg, M. (2002), Manufacturing Strategy: Linking Competitive Priorities, Decision Categories and Manufacturing Networks, PhD thesis, Linköping Institute of Technology.

Rusjan, B. (2005), 'Model for manufacturing strategic decision making', *International Journal of Operations & Production Management* **25**(8), 740–761.

Saunder, M., Lewis, P. & Thornhill, A. (2007), *Research methods for business students*, 4 edn, Pearson Education Limited, Sussex, England.

Semini, M., Fauske, H. & Strandhagen, J. O. (2009), Applications of discrete-event simulation to support manufacturing logistics decision-making, *in* L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol & R. M. Fujimoto, eds, 'Proceedings of the 2006

Winter Simulation Conference', Institute of Electrical and Electronics Engineers, Inc., Trondheim, Norway, pp. 1946–1953.

Silver, E. A., Pyke, D. F. & Peterson, R. (1998), *Inventory Management and Production Planning and Scheduling*, 3 edn, Wiley, John Sons, Inc.

Simon, H. A. (1960), *The new science of management decision*, Harper Brothers.

Speier, C., Valacich, J. S. & Vessey, I. (1999), 'The influence of task interruption on individual decision making: An information overload perspective', *Decision Sciences* **30**(2), 337–360.

Sundkvist, R. (2014), Financial benefits of shop floor improvements, PhD thesis, Chalmers University of Technology.

Sundkvist, R., Hedman, R. & Almström, P. (2012), 'A model for linking shop floor improvements to manufacturing cost and profitability', *International Journal of Computer Integrated Manufacturing* **25**(4-5), 315–325.

Tolk, A., Madhavan, P., Tweedale, J. W. & Jain, L. C. (2009), *Agent-Directed Simulation and Systems Engineering*, WILEY-VCH Verlag GmbH & Co. KGaA, Weinheim, chapter 14, pp. 399–431.

Van Lohuizen, W. C. (1986), 'Knowledge management and policymaking', *Knowledge: Creation, Diffusion, Utilization* **8**(1), 12–38.

von Beck, U. & Nowak, J. W. (2000), The merger of discrete event simulation with activity based costing for cost estimation in manufacturing environments, *in* P. A. Fishwick, K. Kang, J. A. Joines & R. R. Barton, eds, 'Proceedings of the 2000 Winter Simulation Conference', Institute of Electrical and Electronics Engineers, Inc., Piscataway, New Jersey, pp. 2048–2054.

Ward, P. T., McCreery, J. K. & Anand, G. (2007), 'Business strategies and manufacturing decisions: An empirical examination of linkages', *International Journal of Operations & Production Management* **27**(9), 951–973.

Wheelwright, S. C. (1984), 'Manufacturing strategy: Defining the missing link', *Strategic Management Journal* **5**(1), 77–91.

Yin, R. K. (2009), *Case study research, design and methods*, Vol. 5 of *Applied social research methods series*, 4 edn, SAGE Publications, Inc., Thousand Oaks, CA, USA.

Appendix A

List of personal interviews

Appendix A contains a listing of all interviews conducted in the study, divided by internal interviews at Company X and external interviews.

A.1 Internal interviews at Company X

The interviews conducted at Company X are listed in table A1. Due the request of anonymity by Company X, all names of the interviewees at the organisation have been anonymised as well. The real name of the interviewees were instead exchanged by a code name identifying the affiliation and interview number corresponding to the specific affiliation, i.e.:

1) *Factory interviews*: FAC [Factory number]: [Position (shortened)]
2) *Corporate headquarters interviews*: HQ: [Position (shortened)]

Some of the interviews were conducted in groups of two, which can be recognised by the entries containing two positions. As the interviews were conducted simultaneously, the name of the interview were set as one.

Table A1. List of interviews conducted at Company X ordered by the date of interviewing.

Name	**Affiliation**	**Position**	**Date of interview**
FAC 2: Fin. Dept: IT Specialist	Factory 2	IT Specialist - Financial Dept.	7 April 2017
FAC 1: Planning Manager	Factory 1	Planning manager	12 April 2017
FAC 1: Fin. Manager	Factory 1	Financial Manager	12 April 2017
FAC 3: Tech. Manager	Factory 3	Technical Manager	19 April 2017
FAC 3: Prod. Planner	Factory 3	Production Planner	19 April 2017
FAC 2: Tech. Engineer	Factory 2	Technical Engineer	20 April 2017
HQ: Ind. Strat.: BA	Headquarters	Business Analyst - Industrial Strategies	24 April 2017
HQ: Tech. Dev. Manager	Headquarters	Technology Development Manager	24 April 2017
FAC 4: Prod. Planner	Factory 4	Production Planner	26 April 2017
HQ: Proj. Engineer	Headquarters	Project Engineer	10 May 2017

A.2 External interviews

The interviews conducted externally (i.e other than at Company X) are listed in table A2.

Table A2. List of external interviews ordered by the date of interviewing.

Name	**Affiliation**	**Position**	**Date of interview**
Erik Videsson	Implement Consulting Group	Management Consultant - Operational Strategy	18 April 2017
Per Wiklund	AstraZeneca	Capital Project Manager	20 April 2017
Leif Pehrsson	Volvo Car Corporation	Director Manufacturing Research & Concepts	8 May 2017
Johan Marklund	Faculty of Engineering (LTH), Lund University	Professor at the Division of Production Management	9 May 2017

Appendix B

Sample of interview questions

Appendix B contains a sample of the questions addressed to the interviewees during the semi-structured interviews for the internal view. The questions are listed categorised into different topics.

Stakeholder profile

What is/are your:

1) worktitle;
2) organisational level (reports to);
3) working role;
4) responsibility areas;
5) decision mandate (what type of decisions do you make);
6) areas/functions impacted; and
7) experience in investment and/or improvement projects? (If yes, what was your role?)

View on simulation

8) What is your previous experience with simulation/simulation projects?
9) How could simulation be used to improve or analyse your responsibility areas?
10) Could you give some examples of areas/parameters in the production where simulation could be useful for improvement? What would you like to improve?
11) What are the disadvantages/challenges of using simulation as decision-support as you see?

Performance and performance measurement

12) Are your personal performance measured by any PMs? If yes, what PMs?
13) Do you measure and evaluate the performance of your responsibility areas by any PMs? If yes, what PMs?
14) How does performance measurement differ between your and others responsibility areas up and down in the organisation?
15) Which PMs do you consider to be the most important for your responsibility area and the production system in general?
16) What is hard to measure now that you would like to measure if you could?
17) What type of PMs do you see as relevant for your responsibility area and the production system in general?
    i) Financial versus non-financial/operational PMs?
    ii) Outcome versus predictive (action/input/diagnositc) PMs?
18) Depending on the organisation level:
    i) Do you think the type of PMs change , e.g. more aggregated and more financial the higher level?
    ii) Do you think the number of measures change, e.g. fewer measures at higher level?

Improvements

19) Have you proposed any improvement ideas to your managers? If yes, what kind of information did they want/request in order to decide whether to implement it or not?
20) Have people proposed improvement ideas to you? If yes, what information or data did you want/request in order to know whether you should implement it or not?
21) How do you measure the benefits and costs of improvement efforts?
22) What do you typically focus on in your improvement efforts? And what are you most interested in improving? (E.g. cost, productivity, quality, speed, flexibility.)
23) Do you typically try to improve areas with direct impact on performance or the underlying causes/drivers of performance?

Decision-making

24) How would you describe your decision-making? E.g. rational, intuitive, emotional, detail-oriented, information-driven, holistic, short-term/long-term, etc

25) How would you describe other peoples decision-making, at Company X and at the factory?
26) What information and data do you want/need to make your decisions on
    i) new machines, equipment, layout;
    ii) new procedures or processes;
    iii) planning or scheduling;
    iv) batch sizes;
    v) inventory; and
    vi) product mix.
27) Do you measure in some way what the outcome was?
28) Do people you work with typically require a lot of information in order to make a decision? What kind of information?
29) Are there any specific kinds of information that you would have liked to see if you could get them to make better decisions?
30) How do you think the information needed for a decision is affected by the level of the decision-maker?