THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Capturing the Operational Improvement Potential of Production Systems

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ABSTRACT

The operational level is where a company's manufacturing strategy becomes reality and where customer orders are fulfilled through transforming raw materials into finished goods. The research presented here examines the productivity and capacity of operational processes in manufacturing firms. Though both terms are well established in industry, overall, there is ambiguity in their measurement and interpretation across the hierarchal levels of organizations, all the way to the national level. Similar ambiguity is also found in the academic field of operations management, in which much of the related research in recent decades has concentrated on narrow sets of problems, distant from actual shop floor operations.

As a result, many existing approaches to assessing the productivity and capacity of production systems either narrowly focus on certain functions of a production process or address them at such an aggregated level that there is insufficient detail to determine the root causes of production system losses. This leads to the risk that improvement potential at an operational level may be disregarded when strategic decisions are made, making it difficult to improve economic efficiency and preventing the sustainable utilization of a firm's current manufacturing resources. The purpose of this research is accordingly to *increase the understanding of the improvement potential of real operational processes* by developing a framework for identifying and objectively measuring the relevant characteristics of real-life operational processes related to the improvement of shop floor operations. This research, which incorporates five empirical studies, builds on the theory of performance frontiers and on the body of industrial engineering knowledge.

The research illustrates how the analytical logic and structure of the framework can be applied in determining the overall productivity and capacity of firm operations from the micro level and up, by relying on first-order time data measured at the operational level. This establishes a direct link between firm-level capacity utilization and the causes of shop floor productivity losses. It constitutes the foundation on which to build knowledge of the effects on plant-level capacity utilization that come from realizing operational improvement potentials. The results are also intended to provide guidance for decision-making in manufacturing companies.

Keywords: Productivity, Capacity, Capacity utilization

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"Optimist: The glass is half full.
Pessimist: The glass is half empty.
Industrial Engineer: The glass is twice as large as it needs to be."

Göteborg, July 2016

Richard Hedman

LIST OF APPENDED PAPERS

This thesis is based on the work contained in the following papers.

Paper A

Hedman, R., Sundkvist, R., Almström, P., & Kinnander, A. (2013). Object-oriented modeling of manufacturing resources using work study inputs. *Procedia CIRP, 7,* 443–448.

Contributions: Hedman initiated and wrote the paper with Sundkvist and Almström as co-authors and Kinnander as reviewer. Hedman developed the model and the modeling approach, was the corresponding author, and presented the paper at the conference.

Paper B

Hedman, R., Sundkvist, R., Almström, P., & Kinnander, A. (2013). Reference model of manufacturing resources. *Proceedings of the International Conference on Advanced Manufacturing Engineering and Technologies, vol. 2,* Stockholm, Sweden, pp. 221–230.

Contributions: Hedman initiated and wrote the paper with Sundkvist and Almström as co-authors and Kinnander as reviewer. Hedman developed the model and the modeling approach, was the corresponding author, and presented the paper at the conference.

Paper C

Hedman, R., Sundkvist, R., & Almström, P. (2015). Capacity frontiers: Capturing the operational improvement potential of production systems. Submitted to and currently under review by an international journal.

An earlier version of this paper was presented by Hedman at the *26th Annual Conference of the Production and Operations Management Society,* Washington, DC, 2015.

Contributions: Hedman initiated and wrote the paper with Sundkvist and Almström as co-authors. Hedman designed both studies and modeled and analyzed the data.

Paper D

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Contributions: Hedman initiated and wrote the paper with Almström as co-author. Hedman designed the study and collected and analyzed the data.

Paper E

Hedman, R., Subramaniyan, M., & Almström, P. (2016). Analysis of critical factors for automatic measurement of OEE. Presented at the *49th CIRP Conference on Manufacturing Systems*, Stuttgart, Germany, 25–27 May 2016. Forthcoming in *Procedia CIRP*.

Contributions: Hedman initiated and wrote the paper with Subramaniyan as co-author and Almström as reviewer. Hedman designed the study and participated in the data analysis and modeling with Subramaniyan.

Paper F

Hedman, R., & Almström, P. (2015). On the measurement of capacity utilization in industry: A critical reflection from a shop floor perspective. Accepted for a second round of review at *Journal of Business Cycle Measurement and Analysis*.

Contributions: Hedman initiated and wrote the paper with Almström as co-author. Hedman designed the study and modeled and analyzed the data.

LIST OF ADDITIONAL PUBLICATIONS BY HEDMAN

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.

Sundkvist, R., Hedman, R., Almström, P., & Kinnander, A. (2012). Improvement potentials in Swedish electronics manufacturing industry: Analysis of five case studies. *Procedia CIRP*, 3, 126–131.

Hedman, R., Sundkvist, R., Almström, P., & Kinnander, A. (2012). Evaluating manufacturing information models for productivity and profitability assessment of manufacturing facilities. *Proceedings of the 5th International Swedish Production Symposium*, Linköping, Sweden.

Sundkvist, R., Hedman, R., Almström, P., & Kinnander, A. (2012). Understanding cash conversion principles to facilitate and motivate manufacturing development initiatives. *Proceedings of the 5th International Swedish Production Symposium*, Linköping, Sweden.

Almström, P., Kinnander, A., Sundkvist, R., & Hedman, R. (2012). How to realize the productivity potentials in the manufacturing industry. *Proceedings of the 5th International Swedish Production Symposium*, Linköping, Sweden.

Sundkvist, R., Almström, P., Hedman, R., & Kinnander, A. (2013). The effects of factory floor productivity improvements on operational performance metrics. Presented at the *20th European Operations Management Association (EurOMA) Conference*, Dublin, Ireland.

Hedman, R. (2013). Manufacturing resource modelling for productivity management: Towards a better understanding of the productivity improvement potential at shop floors. Thesis for the degree of Licentiate of Technology, Chalmers University of Technology.

Hedman, R., Sundkvist, R., & Almström, P. (2014). Identification of relationships between operator utilization and real process capacity. *Proceedings of the 6th International Swedish Production Symposium*, Gothenburg, Sweden.

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1 Introduction

This chapter presents the practical relevance and theoretical positioning of the research, which constitute the basis for the formulated purpose and research questions. The chapter ends by clarifying key concepts and outlining the thesis.

1.1 Challenges in manufacturing: the practical relevance

Since the industrial revolution, manufacturing has been one of the most important economic activities promoting growth. However, over the last three decades, developed countries in Western Europe and North America have experienced deindustrialization (Szirmai et al. 2013; Rodrique et al. 2014), resulting in considerable job loss and the global redistribution of manufacturing production (UNIDO 2013; Westkämper 2013). Companies in developed countries had already started to face competition from low-wage countries in the 1970s, which contributed to closures and restructurings of primarily labor-intensive industries. In the 1990s, the number of startups and acquisitions in low-wage regions of Southeast Asia and later China increased (UNIDO 2013). After the fall of the Berlin Wall, the low-wage regions of Eastern Europe also became accessible for foreign investment. This increased internationalization and offshoring of production activities was enabled by extensive financial market deregulation, improved information technology, and expanded infrastructure that lowered transportation costs (Bengtsson 2008). The business climate in low-wage countries gradually improved, further facilitating foreign establishments for on-site manufacturing and as a base for subcontractors (UNIDO 2013).

As Europe and North America recover from the latest recession, governments and policymakers, grasping the importance of a strong industry sector for economic resilience, are now concerned about the loss of strategic manufacturing industries. Several initiatives have been launched to promote reindustrialization with the overall objective of creating jobs and maintaining disposable income at the national level (Westkämper 2013; Foresight 2013; Näringsdepartementet 2016). While earlier offshoring strategies were mainly motivated by anticipated cost reductions (Bengtsson 2008; Fill and Visser 2000), the current challenge of reindustrialization is far more complex (Westkämper 2013). Deindustrialization has resulted in a loss of manufacturing knowhow, which has moved to new countries, and finding suitably skilled labor is a bottleneck for reindustrialization initiatives (Westkämper 2013; Foresight 2013; Näringsdepartementet 2016). Cost is still an important factor, but the cost focus has begun to shift from just labor costs to total costs that fully account for global supply networks (Manyika 2012; Rodrique et al. 2014). However, as many low-wage regions have evolved into large markets with developed supply chains and improved infrastructure, traditional national manufacturing companies have become global actors with sites in multiple locations (Manyika 2012; Dachs et al. 2012). This means that there is now global competition even among factories within the same company.

Individual companies are not homogenous entities that respond equally to certain actions. Their ability to compete in various markets is determined by several key attributes (i.e., availability of skilled labor, speed of delivery, and access to raw material and suppliers), some of which are more important than others depending on the industry type (Manyika 2012). Nevertheless, the fundamental objective of any factory is to transform raw material into finished goods, and this conversion process introduces a core concept of this thesis: productivity. Productivity, generally defined as the relationship between input and output, has always been a key driver of competitive development in manufacturing (Tangen 2005). As outlined by Bernolak (1997), "productivity means how much and how good [sic] we produce from the resources used." The manufacturing strategy of an enterprise determines where and how resources are deployed, but it is at the operational level in the factory that strategy becomes reality and that customer orders are filled (Slack and Lewis 2002). High productivity in the operational processes of enterprises in general, and of manufacturers in high-wage regions in particular, is therefore a prerequisite for economic efficiency and the sustainable utilization of resources (Jovane et al. 2008).

The underlying principles of productivity apply to both macroeconomic and microeconomic considerations, meaning that it is a relative concept (Bernolak 1997). At the national level, output is measured as gross domestic product (GDP), while firm-level output typically refers to the quantity or value of the products produced (Obstfeld et al. 1996). In these cases, the industry or firm is seen as the transformation entity and inputs constitute multiple factors, typically capital, labor, materials, and energy (Prokopenko 1987). In firms, top managers have a strategic perspective on productivity that differs from the more operational view of the shop floor (Tangen 2005). The means of achieving high productivity may therefore be level specific, ranging from focusing on the actual and potential output of a production process to optimizing the allocation of resources between manufacturing sites (Tangen 2005; Prokopenko 1987; Coelli et al. 2005). However, this understanding can lead to confusion and misconceptions. Bernolak (1997) argues that most managers do not know what productivity really means and therefore do not know how to measure and analyze it. Tangen (2004) states that people are generally unaware that different definitions of productivity are used simultaneously.

Strategic decisions to offshore production activities made by many European companies were based on the perception that improving the productivity of existing production processes in the original company had only limited potential to cut costs and increase capacity (Dachs et al. 2006). This perception at the beginning of the millennium is today acknowledged to have led to decisions with only short-term benefits (Westkämper 2013). The results of extensive measurements of shop floor productivity in Swedish industry between 2005 and 2011 reveal that the possibility of decreasing costs and increasing capacity by improving productivity at the operational level had been neglected, and that the improvement potential is often considerably higher than company management imagines (Almström and Kinnander 2011, 2008). While firm-level productivity can be calculated using the same type of data used in accounting and financial management (i.e., resource cost, worked hours, and output quantities), productivity measures at the operational level are dependent on the systematic measurement and analysis of shop floor operations (Prokopenko 1987). It is clear that the representation of actual shop floor productivity in higher-level measures has suffered from a decline of work studies in industrial engineering and a shift of focus from the operational level (Almström and Kinnander 2011; Bailey and Barley 2005). Together with the overall ambiguity in the measurement and interpretation of productivity, this means that even future strategic decisions in companies may be made without sufficient knowledge of actual conditions and potentials at the operational level. Consequently, the challenge is to ensure that operational improvement potential is not neglected when strategic decisions are made, and this challenge provides the practical relevance of this research.

1.2 The research field

This research belongs to the operations management (OM) field, which covers the application of resources to the production and delivery of products and services. OM is thus concerned with the tactical actions taken to plan, schedule, and control activities (Slack et al. 2010). As an academic discipline, OM has been evolving since the era of "scientific management," and besides manufacturing, now also includes areas such as service, healthcare, retail, and transportation (Walker et al. 2015). The OM field is broader than the scope of this thesis, which primarily concerns the measurement and modeling of shop floor operations and the improvement of operational processes.

Microeconomic theory is usually employed in OM to model and analyze differences in productivity and performance among firms (Fisher 2007). Schmenner and Swink (1998) have noted that while microeconomic theory can be applied in OM to provide help to understand differences in observed productivity among firms, it is limited as a complete explanation of these differences. In response, Schmenner and Swink (1998) formulated the theory of performance frontiers, derived from microeconomic theory and from the empirical and deductive laws of manufacturing system behavior. It constitutes the main theoretical foundation of which the findings of this thesis have been elaborated.

Productivity as a performance measure requires quantification of the efficiency or effectiveness of actions (Neely et al. 1995). Performance measurement originates in the studies of workers, their work, and management conducted by Frederick W. Taylor (1911) and in subsequent studies of motion, skill, fatigue, and management psychology by the Gilbreths (Mousa and Lemak 2009). The systematization and standardization of shop floor operations together with driven conveyer belts were among the key success factors for Henry Ford's assembly lines (Wilson 2013). It was these ideas that later inspired Japanese industry (Robinson and Robinson 2003) and the development of the widely cited Toyota Production System (Ohno 1988). Mass production in the United States accelerated during World War II, when knowledge from earlier shop-floor studies was used in combination with engineering methods and statistical process control (Sprague 2007). This set the stage for the post-war direction of OM, which involved the introduction and application of analytical methods from operations research (OR), such as mathematical programming, queuing theory, and simulation (Hopp and Spearman 2008).

According to Slack et al. (2004), the scholarly contribution of OM has been to identify, model, and categorize empirical phenomena. Early-twentieth-century studies of work provided OM researchers with an empirical understanding of operational processes (Bertrand and Fransoo 2002). Starting in the 1950s, further developments in work measurement resulted in universal standard data for work measurement and predetermined time standards (Zandin 2001a; Niebel and Freivalds 2003). However, OM research has recently focused on increasingly narrow sets of problems (Sprague 2007; Slack et al. 2004). Many of these problems are idealized and distant from actual shop floor operations and, consequently, are of little relevance to industrial implementation or real managerial issues (Bertrand and Fransoo 2002; Meredith 1993).

Meredith et al. (1989) identified the shortcomings of past OM research as narrow instead of broad scope, focus on techniques instead of on knowledge, and abstract instead of real perspective. Though these shortcomings were identified almost three decades ago, there is still ongoing debate concerning the practical relevance of OM research output (MacCarthy et al. 2013; Taylor and Taylor 2009) and a need to close the gap between theory and practice in the OM community has been identified (Schmenner et al. 2009; Sprague 2007). In addition, in a systematic review of the past three decades of literature on performance measurement systems, Choong (2014) identified a research gap specifically related to performance measurement, noting great overlaps in the meanings and definitions of terms related to data and measurement attributes. Choong (2014) concludes that, overall, there is no consensus about what to measure and what to communicate to stakeholders.

1.3 Main research purpose and objective

The purpose of this research is *to increase the understanding of the improvement potential of real operational processes.* This purpose was formulated to meet the academic challenge of increasing the usability and relevance of OM research, in particular, of addressing problems related to effective performance measurement and the improvement of shop floor operations. The research also addresses the industrial challenge of ensuring sustainable resource utilization and the high productivity of operational processes, which require that operational improvement potential not be neglected when strategic decisions are made.

The objective is to contribute to existing OM knowledge by providing a framework for identifying and objectively measuring the relevant characteristics of real-life operational processes related to the improvement of shop floor operations.

1.4 Research questions

Based on the purpose and objective, three research questions have been formulated:

RQ1: What key constructs are needed to describe the operational improvement potential of a production system?

RQ2: How can the key constructs be represented in an integrated model to explain the operational improvement potential of a production system?

RQ3: How can the operational improvement potential be captured to support decisions about improvement initiatives?

Research question one concerns what to measure and how to measure it in order to capture the most relevant characteristics of a production system related to its operational improvement potential.

Research question two addresses how the acquired data should be *conceptually* organized as information in a generic production system model.

Research question three builds on research questions one and two and addresses how the operational improvement potential should be captured *in practice*. In this context, "capture" means "to succeed in representing or expressing something intangible," as defined in the *Cambridge Dictionary of English* (Procter 1995).

1.5 Delimitations

Performance measurement and performance measurement systems constitute a large research field in itself owing to the many different performance measures (Neely et al. 1995; Choong 2014). In this thesis, performance measurement focuses on shop floor productivity, particularly the improvement of shop floor productivity in the interest of increasing capacity. Sundkvist (2014) noted that increasing capacity is among the most common objectives of production-improvement initiatives.

The term *resource* is limited to humans (i.e., labor) and equipment, aligned with the international standard for manufacturing data management (MANDATE) (ISO 2005). Resources in terms of energy and material are not considered.

In addition, this research concerns measuring and improving operations in existing production systems and, consequently, does not cover performance evaluations or the design of new production systems.

1.6 Thesis outline

The thesis is structured according to the outline presented in Table 1.1.

Table 1.1. Thesis outline

Chapter	**Content**
1. Introduction	The first chapter presents the practical relevance and theoretical positioning of the research. These provide a basis for the purpose and research questions formulated.
2. Frame of reference	The second chapter introduces the theoretical foundation of the thesis. Theory of production systems, shop floor data, productivity, and capacity are discussed. The theory of Performance frontiers of which the proposed framework is based upon is also presented. The chapter ends by describing the research gap.
3. Methodology	The third chapter describes how the research has been conducted by presenting the research process in relation to the adopted view of science. The main research methods and techniques used are also described.
4. Results	The fourth chapter sums up the results of the appended papers, focusing on the contributions to answering the research questions.
5. Discussion	The fifth chapter covers the discussion of how the main results relate to the research questions and the objective of the thesis. This is followed by

	discussion of the academic contribution and industrial relevance of the research.
6. Conclusions and future research	In the sixth and final chapter, the main conclusions are presented together with suggestions for future research.

2 Frame of reference

This chapter introduces the theoretical foundation of the research. Theories of production systems, shop floor data, productivity, and capacity are discussed. The theory of performance frontiers, on which the proposed framework is based, is also presented. The chapter ends with a brief summary and a problem formulation.

2.1 Production systems

It is generally acknowledged that applying a systems perspective facilitates the description and understanding of production systems (Bellgran and Säfsten 2009). Modern system studies originate from the general system theory (GST) of Ludwig von Bertalanffy (Von Bertalanffy 1950). A system is often defined as a number of components forming a whole that differs from the sum of the components themselves (see, e.g., Blanchard et al. (1990); Wu (2012); Dekkers (2015). System theory combines a number of principles used to describe and explain complex phenomena in which a single component cannot be understood without considering its context (Von Bertalanffy 1950). This view, i.e., that the whole is more than the sum of its parts, is referred to as the principle of holism and its formulation dates to the time of Aristotle (Skyttner 2005). Reductionism, which can be seen as the opposite to holism, is when complex phenomena are reduced to simpler structures and the whole is understood by analyzing its parts (Skyttner 2005). However, to obtain a better understanding of complex systems, reductionism and holism are sometimes incorporated as complementary strategies (Anderson 1999).

Production systems can be classified according to three perspectives corresponding to the functional, structural, and hierarchal concepts (Bellgran and Säfsten 2009). Viewed in isolation, these perspectives might each lead to specialized theories, but they can be connected and unified within GST (Skyttner 2005). In the functional concept, the system is viewed as an entity that transforms inputs to outputs and the function describes the purpose of the system (Dekkers 2015). It is not difficult to relate this to the fundamental objective of a production system, which is to transform raw material into finished goods (Hopp and Spearman 2008). Boer et al. (2015) argue that it is this process of converting inputs to outputs that underpins virtually everything done in the OM discipline. The functional concept typically involves a “black-box” approach in which the external structures of a system are investigated but without identifying any of the internal components (Bellgran and Säfsten 2009). The behavior of the system is thereby analyzed as if it were a single component (Dekkers 2015).

In the structural concept, aligned with the principle of holism, a system comprises a set of elements and a set of relationships between them (Von Bertalanffy 1950). These elements can be physical objects as well as theoretical constructs, and the relationships describe the dependencies among them (Dekkers 2015). A structural view of a production system can, for example, refer to the descriptions and relationships between personnel and machines on the shop floor (Bellgran and Säfsten 2009). Finally, the hierarchal view of systems implies that a system can constitute a subsystem of a larger system (Skyttner 2005). For a production system the hierarchical view often refers to organizational levels, such as the operational, tactical, and strategic levels employed in operations strategy (Slack and Lewis 2002) or, as in the example cited by Bellgran and Säfsten (2009), to a production system consisting of one production system and one assembly system. The structural concept can turn into the hierarchal concept if the elements are themselves regarded as nested subsystems (Skyttner 2005).

A production system is an open system and thereby interacts dynamically with the surrounding environment (Bellgran and Säfsten 2009). A system boundary is used to distinguish between the environment and what is inside the system; it also represents the contact point between the system and other systems (Wu 2012). According to Bellgran and Säfsten (2009) and Wu (2012), production systems are goal seeking and their various subsystems differ in their importance for goal fulfillment. They are also characterized by equifinality, meaning that the goal or an end state can be reached in many ways.

2.1.1 Production system modeling

Models of production systems are found in a variety of fields, such as process planning (Feng and Song 2003), performance measurement (Mathur et al. 2011), manufacturing resource capability modeling or selection (Vichare et al. 2009), business process modeling (Giaglis 2001), and modeling for manufacturing system design (Bellgran and Säfsten 2009; Wu 2012). As modeling approaches differ in how they cognize the real world, the key is to understand where an approach does and does not apply. Modeling methods and languages can be based on one or several modeling approaches. In the following, two specific modeling languages of interest are presented.

Unified modeling language (UML) provides several types of graphic modeling diagrams mostly targeting systems modeling but also used to model production processes (Dekkers 2015). UML has become an industry standard for modeling software-intensive systems (OMG 2011). It is based on the object-oriented approach and therefore considers both data and functions that enable a picture of the whole process and the associated actors and processes. An object represents real or intended things and a class defines the object’s properties and behaviors. The UML language’s notations and rules are designed to represent data requirements in terms of object-oriented models. Use case diagrams can be created to capture a system’s functionality and class diagrams to capture its vocabulary. There are also several kinds of diagrams used to describe system behavior and to represent implementation, interaction, and deployment activities.

The EXPRESS modeling language is part of the Standard for the Exchange of Product model data (STEP) and is defined in ISO 10303-11. It is usually used for integration between different manufacturing system applications, often with an orientation toward machining (ISO 1994). It consists of language elements that allow unambiguous data definition and the specification of constraints on the data defined and is based on the object-oriented approach. It uses a textual representation with graphic subsets available; this graphic representation is called EXPRESS-G.

2.2 Shop floor data acquisition

The operational improvement potential of a production system cannot be captured without acquiring data. This section introduces some of the traditional work measurement techniques that are fundamental for studying manual work. An overview of automatic systems for the acquisition, modeling, and communication of manufacturing data is also presented.

2.2.1 Time data determination and work measurement

Time data must be determined to set requirements and develop standards for process planning and design at the operational levels of a plant (Kuhlang et al. 2014). They also constitute the foundation for developing and applying measures for production planning, followup, and control at the tactical and strategic levels (Dionne and Kempf 2011; Lödding 2012).

Three principal approaches to determining time data for manual activities are based on historical records, direct time studies, and time studies using predetermined time systems (Niebel and Freivalds 2003). Historical records do not indicate how long an operation should have taken but only how long it actually took (Niebel and Freivalds 2003). Direct time studies are employed to measure operation cycle times based on the presence of a real observation environment (Saito 2001). These studies employ a stopwatch technique in which the durations of all subtasks are measured and then summed to calculate the total operation duration. Besides measuring operation times for planning purposes, direct time studies can also be used for performance rating in which the speed of work is assessed in relation to the defined standard time for that work task (Niebel and Freivalds 2003).

Predetermined time systems is a motion-based technique in which the operation times are created using sequences of building blocks in which target times are assigned to single motion elements. Of over fifty predetermined time systems, the methods-time measurement (MTM) (Maynard et al. 1948) and Maynard operation sequence technique (MOST) are the most common system families (Niebel and Freivalds 2003). In MTM-based systems, elements are expressed as time measurement units (TMUs), each corresponding to 36 milliseconds. Many Swedish companies use the sequence-based activity and method analysis (SAM) MTM-based system (IMD 2004). While direct time studies require real-life observations, predetermined time systems can be applied in designing activities and determining their duration even though an operation exists only on paper during the planning phase. Nevertheless, for defined work content, there is a tradeoff in the accuracy needed to determine time data and the effort required to use predetermined time systems (Czumanski and Lödding 2016; Kuhlang et al. 2014). MTM-1 is an example of a very detailed time determination method with a ratio of 1:200, meaning that it would take 200 minutes to analyze one minute of work content (Niebel and Freivalds 2003). For a less detailed predetermined time system, MTM-SAM has a ratio of 1:25–30 (IMD 2004). Recent research initiatives have attempted to automate the required data collection and analysis by applying motion capture systems and augmented reality (e.g., Sung et al. (2015)).

For automatic activities, historical records and direct-time studies can also be applied for time data determination. Direct-time studies are then incorporated to measure the time duration for each produced unit when an individual equipment resource is operated in isolation and under stable processing conditions, i.e., unaffected by factors such as blocking, starvation, and disturbance (Hedman et al. 2014). Theoretical cycle times are typically derived based on information from the equipment supplier. However, an efficient way to derive cycle times is through the use of production planning software, such as computer-aided manufacturing (CAM) software (Yusof and Latif 2014).

Work sampling is a statistical technique developed by Tippett (1935) in which random objects are studied at fixed time intervals or fixed object sequences are studied at random time intervals. It is applied to determine the amount of time a resource spends performing defined activities in order to derive a measure of work distribution (Zandin 2001b). It is possible to conduct work sampling studies of both manual and automatic activities as well as of administrative work (Niebel and Freivalds 2003; Murgau 2009). The data collection can be performed both by analysts who observe work and through self-reporting (Niebel and Freivalds 2003).

2.2.2 Automatic data acquisition

Modern systems for automatically acquiring shop floor data have increased the amount of data collected in industry and cover both the organization and communication of the acquired data. The digitalization of industry is greatly emphasized in several ongoing reindustrialization initiatives (Rübmann et al. 2015; Näringsdepartementet 2016; Westkämper 2013), meaning that the volume of shop floor data collected will continue to increase. Digitalization has also led to the formulation of new concepts related to smart factories, sometimes referred to as new manufacturing paradigms, for example, the industrial Internet of things (Da Xu et al. 2014), cloud manufacturing (Zhang et al. 2014; Helo et al. 2014), and the fusion of the physical and virtual world in cyber–physical systems, which is a key design component of Industrie 4.0 (Hermann et al. 2015).

One of the most-established current architectures for shop-floor data acquisition is the ISA95 standard for enterprise control system integration, which defines a manufacturing organization in a five-level functional hierarchy model (Figure 2.1) (ISA95 2013). Sensors and programmable logic devices (PLCs) that monitor and control the actual production processes correspond to the model’s lower levels, i.e., levels 0–2. Manufacturing operations management, comprising manufacturing execution systems (MESs), refers to the third level in this hierarchy. It models the management of production, maintenance, quality, and inventory operations. Its objective is to optimize manufacturing processes and resources and to provide higher-level systems, i.e., enterprise resource planning (ERP) systems, with manufacturing data so they can manage enterprise operations, such as business planning and logistics.

Moreover, two international standards associated with the ISA95 standard target the organization and communication of shop floor data: ISO 10303-11 and ISO 15531 (Chen and Vernadat 2004). ISO 10303-11 is the Standard for the Exchange of Product model data (STEP), which is used to exchange data between systems for computer-aided design, manufacturing, and engineering (i.e., CAD, CAM, and CAE) (Feng and Song 2003). ISO 15531 is the international standard for manufacturing data management (MANDATE) and defines production and resource information (ISO 2005). Both standards use the EXPRESS modeling language described in the previous section.

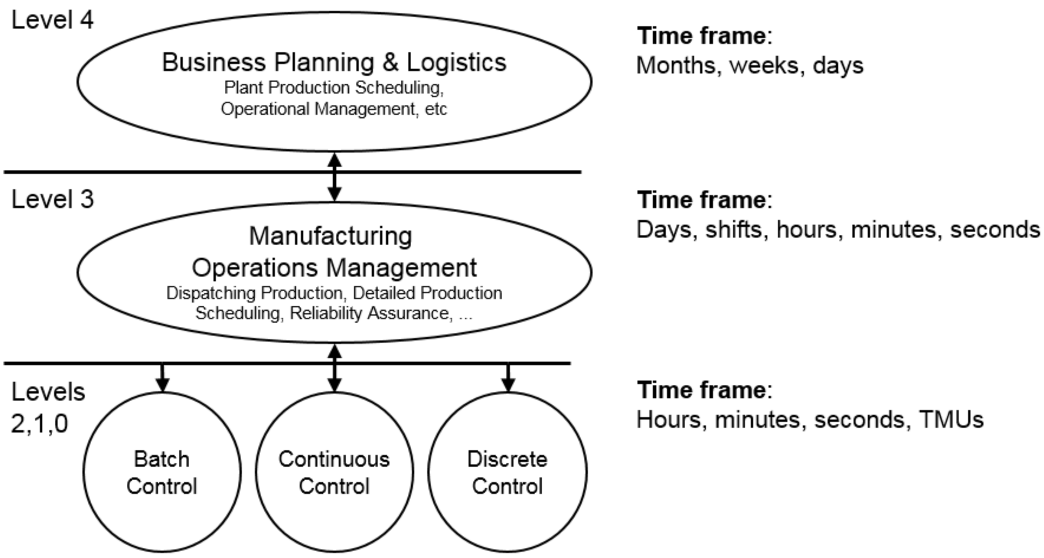

Figure 2.1. Functional manufacturing hierarchy; adapted from ISA95 (2013).

2.3 Productivity and capacity

Productivity and capacity are two central concepts frequently cited throughout this thesis. Even though these terms are used in an industrial context, they are interpreted differently depending on whether one is speaking with an economist or a production engineer.

2.3.1 Firm-level productivity

Productivity changes are movements in the productivity performance of a nation, or the sectors of a nation's economy, over time (Bernolak 1997). They can refer to either total factor productivity, which includes all production factors, or partial productivity measures, such as labor productivity (Coelli et al. 2005). Economists typically employ production functions to model and analyze productivity (Coelli et al. 2005; Bernolak 1997). It is common to use the term *frontier* to emphasize that the production function gives the *maximum* output that is technological feasible (Coelli et al. 2005). Inputs are typically classified as capital, labor, and other, while the outputs involve information about output quantities and price. Some of the most common techniques used, based on the concept of production functions, are data envelopment analysis (DEA) and the stochastic frontier approach (Singh et al. 2000; Coelli et al. 2005). Several of these techniques are incorporated at the microeconomic level, but the focus is on the performance of individual firms rather than of the economy as a whole (Chen et al. 2015). As stated, output is then measured in quantities, such as produced goods, sometimes also including price information.

Plant productivity corresponds to how efficiently a firm utilizes its input to produce output (Bernolak 1997; Tangen 2003). Production economists are therefore primarily interested in input and output quantities, together with their respective prices and quality characteristics (Rasmussen 2012). As the entire firm is viewed as the entity that transforms inputs to outputs, aggregate descriptions of technology are used (Rasmussen 2012). Production economists also focus on assessing firms, for example, by investigating a firm's performance compared with that of its competitors, and on whether a firm has improved its productive capacity over time

(Rasmussen 2012). The relative performance of a firm is measured in terms of its distance from the industry's efficient frontier, which is in turn estimated based on the (observed) inputs and outputs from a representative sample of the firms in a given industry (Coelli et al. 2005). This approach addresses allocative efficiency, which describes the ability of firms to use their inputs in optimal proportions, given the respective input prices and the available production technology (Färe and Zelenyuk 2003). A firm can be technically efficient but may still be able to improve its productivity by exploiting scale economies (Coelli et al. 2005). Balk (2001) has identified three primary sources of total factor productivity growth at the firm level:

- technical change resulting from a shift in production technology
- efficiency change associated with the firm's ability to use the available technology and to make more efficient use of its inputs
- scale efficiency change, referring to improvements in the firm's scale of operations

Prokopenko (1987) categorizes the factors affecting the productivity of a firm as either external or internal. External factors are beyond the control of the individual company. They correspond to macro-productivity factors, such as social and structural changes, economic changes, and government policies and infrastructure. Internal factors are controllable and include what Prokopenko (1987) calls hard factors (i.e., fixed assets, materials, and products) and soft factors (i.e., people, management policies, and organization).

2.3.2 Capacity

Capacity measures the output that can be produced with the available resources of a manufacturing facility. The concept of capacity plays a central role in long-term production planning and short-term activity scheduling (Hopp and Spearman 2008). Productivity is always defined as the relationship between input and output, even though the measurement and interpretation of productivity differ depending on the context in which the concept is used. In contrast, as there is overall ambiguity in the fundamental definitions of capacity (Perry 1973; Elmaghraby 2011), Elmaghraby (2011) stresses that it is vital to define what is meant by capacity as a prerequisite for its measurement.

At the highest level, capacity, also called productive capacity, equals the maximum possible output of an economy (Nelson 1989). Production economists define plant-level capacity as the maximum output level than can be produced with existing plant and equipment (Johansen 1968; Coelli et al. 2002). Individual applications of these definitions may differ, however, in the extent to which they consider labor availability, material supply, and other variables related to plant capacity. The actual output of a plant relative to a measure of full capacity is defined as capacity utilization, or the capacity utilization rate (Klein et al. 1973). The capacity utilization of an industry, or industry group, is an aggregate of plant-level measures and is typically used in business cycle analysis. It is intended to indicate how well productive capabilities are being utilized, with low levels of capacity utilization indicating slowing economic activity and high levels suggesting strong activity and therefore inflationary pressures (Corrado and Mattey 1997; Greenwood et al. 1988).

In production planning and control, Elmaghraby (2011) states that not one but many capacities are used in practice, defining them as nominal capacity, operational capacity, planned capacity utilization, and actual utilized capacity. The nominal capacity corresponds to the productive capability assuming continuous availability of manufacturing resources; it is also referred to as theoretical or maximal capacity. The operational capacity is the productive capability when anticipated losses have been subtracted from the nominal capacity. Elmaghraby (2011) argues that these unavoidable losses include the optimal setup time, or changeover time, between products and the standard rate of rejects (i.e., quality yield). Finally, the planned capacity utilization is the actual utilized capacity as a proportion of the operational capacity that is planned to be used, which naturally corresponds to what is actually utilized in transforming input to output.

2.3.3 Shop floor productivity

In firms, production and industrial engineers are concerned with the design, improvement, and installation of integrated systems of personnel, materials, equipment, and energy (Zandin 2001a), leading to a focus on internal productivity factors. This focus leads to actions such as resource optimization, lead time reduction, and other initiatives to improve productivity and increase capacity. Most previous research into how to measure and improve shop floor productivity is related to many of the well-known continuous improvement methodologies such as Lean Production, Total Quality Management (TQM), and the hybrid approaches of Lean and Six Sigma (Bhamu and Sangwan 2014; Muthiah and Huang 2006; de Mast and Lokkerbol 2012). Schmenner and Swink (1998) have formulated the theory of swift and even flow, giving the theoretical basis for the relationship between Lean Production and productivity (Boer et al. 2015). The theory posits that the swifter and more even the flow of materials through a process, the more productive the process is (Schmenner and Swink 1998). It follows that productivity should increase with the speed of material flow through a process, and decline with increases in the variability associated with the flow.

Productivity on the shop floor level is defined as the ratio of potential output to actual output of a process (Prokopenko 1987). In OM and OR queuing theory, the conventional approach to understanding the performance of operational processes and much previous research in this area have specifically focused on automatic and equipment processes (Walker et al. 2015). Formulas used to calculate the operating characteristics of a system assume that the arrival process as well as the service time are stochastic and characterized by specific statistical distributions with known parameters (Blanchard et al. 1990). For example, Godinho Filho and Uzsoy (2013) combine system dynamics with queuing models to examine the potential outcomes of improvement projects. Mauri et al. (2010) have developed a parameter for operating system effectiveness that detects causes of low productivity to be used when implementing process improvement measures. Similar approaches are also found in the axiomatic model-based research, for example, of Li and Meerkov (2008), Curry and Feldman (2011), and Hopp and Spearman (2008).

Aligned with the theory of swift and even flow, Hopp and Spearman (2008) state that factors that negatively affect shop floor productivity and, consequently, capacity are usually related to variability. They further argue that the principal sources of variability can be classified into two categories: flow variability and process variability. Flow variability is caused by variation arising when jobs are either entering or leaving a system, or when jobs are moving between work stations. This is associated with the design of the production system and with the planning and control policy adopted by management. Process variability is caused by natural variation in process times and by variability arising from preemptive and non-preemptive outages. The difference between preemptive and non-preemptive outages concerns the extent to which it is possible to control the event causing the outages.

Hopp and Spearman (2008) model the interactions among types of variability by combining queuing theory and Little's law (Little 1961), which essentially defines the relationship between work in process (WIP), throughput rate, and cycle time. This constitutes the foundation for what they define as the law of best-case performance for an operational process. It is divided into the best-case cycle time (Equation 2.1) and best-case throughput rate (Equation 2.2):

$$CT_{best} = \begin{cases} T_0 & if\ w \leq W_0 \\ \frac{w}{r_b} & otherwise \end{cases} \qquad (2.1)$$

$$TH_{best} = \begin{cases} \frac{w}{T_0} & if\ w \leq W_0 \\ r_b & otherwise \end{cases} \qquad (2.2)$$

where w is a given WIP level and W_0 is the critical WIP level. The raw processing time is expressed as T_0 and the bottleneck rate as r_b.

Saito (2001) and Helmrich (2003) have defined three dimensions of productivity to better understand what factors to measure and assess when seeking to improve the productivity of shop floor operations. The method factor (M) describes how an operation, or work content, should be executed. It is calculated as the inverse of the ideal cycle time for the specific work task and corresponds to the ideal, or intended, productivity rate of an operation. The performance factor (P) refers to the speed of the operation in relation to its ideal cycle time, i.e., working faster or slower than normal. The utilization factor (U) represents how much of the available working time is spent on the intended method and incorporates aspects of the degree of resource utilization. Table 2.1 presents Saito (2001) compilation of techniques and actions that can be used for assessing each factor. This approach has been used in productivity improvement initiatives in combination with value stream mapping (Kuhlang et al. 2011) and in the PPA studies that, as stated, underlie much of the research presented here (Almström and Kinnander 2011).

Furthermore, one of the best-established specific performance measures for automatic activities, often associated with productivity, is overall equipment effectiveness (OEE) (Jonsson and Lesshammar 1999; Andersson and Bellgran 2015). The OEE measure typically serves as an important driver of improvement initiatives and has been developed to capture losses related to downtime, speed, and quality. OEE is essentially defined as the ratio between the time spent producing goods of approved quality and the scheduled time (i.e., loading time) (Nakajima 1988), formulated as follows:

$$OEE = Availability \times Performance\ efficiency \times Quality\ rate \qquad (2.3)$$

Availability is calculated as the planned production time minus downtime (i.e., breakdowns and changeovers). Performance efficiency is the ideal cycle time multiplied by the number of products produced during actual runtime. The quality rate is the ratio between the number of quality-approved products and the total number of products produced. In relation to the three dimensions of productivity, the OEE measure can be seen as equivalent to the P and U factors multiplied by the quality yield for equipment activities (Almström and Kinnander 2011).

Table 2.1. Techniques and actions for analyzing productivity losses; adapted from Saito (2001).

		Operator	**Machine**	**Material**
Method factor	Actions	• Confirm percentages for basic functions • Estimate the operator reduction factor	• Determine actual machine time • Estimate the potential for reducing machine time	• Determine losses caused by production design • Estimate the potential (%) for improving yield
	Techniques	• Work sampling • Direct time study • Pitch diagrams • Human–machine charts • 4W (i.e., what, who, why, and where) charts	• Pitch diagrams • Sequence charts	• Design review • Value-added analysis
Performance factor	Actions	• Confirm present performance level • Estimate performance improvement potential (%)	• Confirm the facility performance • Estimate the performance improvement potential (%)	• Confirm the quality of materials and parts • Estimate potential to increase first-pass yield
	Techniques	• MOST or MTM analysis • Direct time study • Output analysis	• Work sampling • Material analysis	• Yield analysis • Analysis of failure causes • Analysis of materials
Utilization factor	Actions	• Confirm utilization loss • Estimate the potential (%) for improving the utilization factor	• Confirm utilization loss • Estimate the potential (%) for improving the utilization factor	• Confirm utilization loss • Estimate the potential (%) for improving the utilization factor
	Techniques	• Analyze setup procedures • Investigate the impact of staffing changes • Work sampling	• Downtime analysis • Work sampling • Analyze space utilization	• Scrape rate analysis • Inventory analysis • Investigate alternative materials

2.4 The theory of performance frontiers

The manufacturing strategy literature defines the link between manufacturing objectives and market requirements as competitive priorities constituting the dimensions of quality, delivery, cost, and flexibility (Slack and Lewis 2002). Operational measures of manufacturing performance typically coincide with the manufacturing objectives and their corresponding dimensions (Slack and Lewis 2002). Manufacturing capabilities are characterized by the set of practices in use at a firm and constitute the basis of operational performance. These capabilities can be defined as a plant's actual performance relative to that of its competitors (Schoenherr et al. 2012). They are often conceptualized as the intended or realized competitive performance of a business unit and are assessed using operational performance measures (Flynn and Flynn 2004). Though all performance dimensions are to some extent vital to all operations, which one is the most important is a matter of competitive positioning (Ward et al. 1998). Nevertheless, there is ongoing debate as to whether firms improve manufacturing performance in a cumulative manner or trade off one measure against another, such as cost versus quality or cost versus flexibility (Schroeder et al. 2011; Amoako-Gyampah and Meredith 2007).

In the theory of performance frontiers, output is expanded to include all dimensions of manufacturing performance and inputs to include choices affecting the design and operation of a manufacturing firm. A performance frontier is defined as "the maximum performance that can be achieved by a manufacturing unit given a set of operating choices" (Schmenner and Swink 1998). Tradeoffs and cumulative improvements are not seen as mutually opposed, but rather constitute functions of a firm's positioning relative to its maximum performance frontier (Schmenner and Swink 1998). Using a cost–performance diagram (Figure 2.2), Schmenner and Swink (1998) illustrate two types of performance frontiers: one formed by choices in plant design and investments (i.e., the asset frontier) and another formed in plant operations (i.e., the operating frontier). The performance of a plant is bounded by its operating frontier, which is in turn bounded by its asset frontier.

Schmenner and Swink (1998) argue that the theory can be applied for strategic comparisons both between and within firms. If sufficient slack is available and a firm is positioned below its operating and asset frontiers, it can make simultaneous improvements along multiple performance dimensions without negatively affecting other dimensions. However, as firms become more efficient and remove slack from their systems, it becomes increasingly difficult to make improvements simultaneously in multiple dimensions without negatively affecting other dimensions. This suggests that firms are subject to tradeoffs and have to choose between competing priorities when they are at the frontier.

In Figure 2.2, the left panel shows two firms, A and B, which have similar investments in plant design and technology and therefore share an asset frontier. Firm B, however, employs different management policies and operates closer to its asset frontier than does Firm A, which implies that Firm B makes more efficient use of its inputs than does Firm A. The right panel in Figure 2.2 illustrates how one firm can move, or reshape, its operating frontier by altering manufacturing operating policies, a process that Schmenner and Swink (1998) refer to as "betterment." In comparison, Schmenner and Swink (1998) distinguish "improvement" as what happens when a firm removes inefficiencies in transformation processes without making any changes in its operating policy or physical assets and, consequently, does not alter the shape of the frontiers.

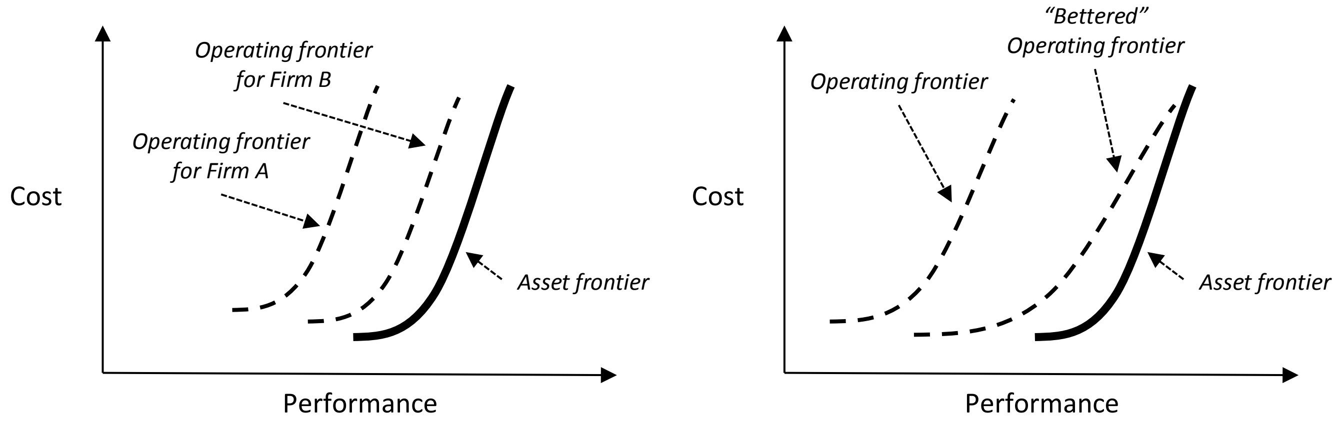

Figure 2.2. The concept of performance frontiers; adapted from Schmenner and Swink (1998).

The theory of performance frontiers was extended by Vastag (2000) two years after Schmenner and Swink (1998). In this extension, Vastag (2000) identified similarities between the definitions of the performance frontiers and terms traditionally used in capacity management, in which the asset frontier can be interpreted as the design capacity of a plant and the operating frontier as the actual output, or effective capacity. Vastag (2000) further argued that cost belongs to the performance dimension, so the diagram is rearranged to depict the performance dimension on the vertical axis and the input dimension on the horizontal axis (Figure 2.3). The stepwise shape of the asset frontier symbolizes asset-related performance improvements. The operating frontier is represented as a concave trajectory path, its downward drops illustrating the initial performance decreases that may occur when introducing new technology or new ways of working. Its shape also reflects the aggregate learning effects of resources, which are central to learning curve theory (Adler and Clark 1991).

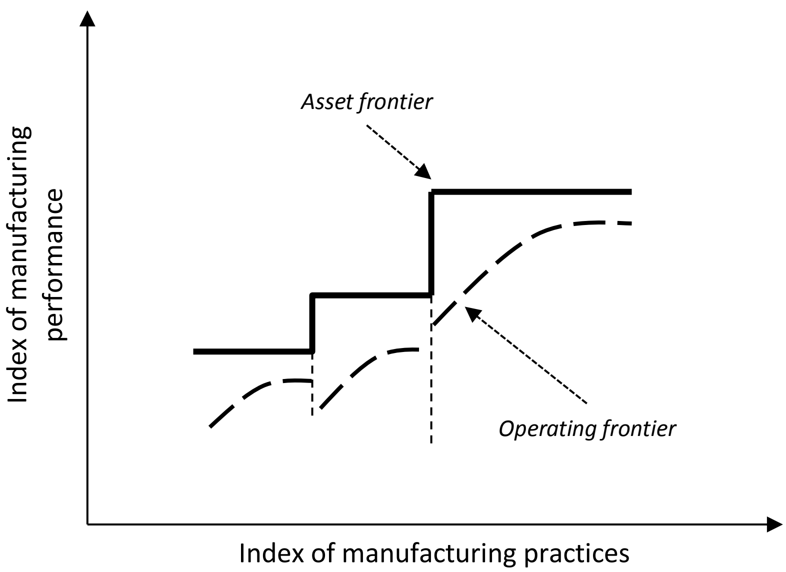

Figure 2.3. The redesign of the performance frontier diagram; adapted from Vastag (2000).

2.5 Research gap

This section has established the theoretical foundation for the research presented here. It has covered the description and modeling of production systems, including how to acquire shop floor data to capture the operational improvement potential. As the overall focus is on the improvement of shop floor productivity in the interest of increasing capacity, the basis for defining and measuring productivity and capacity has been presented.

The theory of performance frontiers has the ability to provide explanatory insight into productivity differences within and between firms (Schmenner and Swink 1998) and is well established in the OM community (Boer et al. 2015; Walker et al. 2015). While the concept of performance frontiers is conceptually elegant, previous research has identified several challenges that limit the practical applicability of the theory. These mainly concern how actually to measure a manufacturer's position relative to a performance frontier. Sarmiento et al. (2008) argued that it is unclear whether performance frontiers and the phenomena that take place inside their boundaries should actually be measured and, if so, how they should be measured. Cai and Yang (2014) stated that it is difficult, if not impossible, to measure the asset and operating frontiers directly in terms of their possible output levels.

In the original paper, Schmenner and Swink (1998) suggested metrics thought to proxy for slack by, for example, measuring nearness to a product range or product cost frontier using a metric based on the ratio of throughput time and processing time. In extending the theory, Vastag (2000) defined the inputs of manufacturing practices based on item-level measurements that are aggregated to an index using summed scales or factor scores. However, how this is to be conducted in practice was outside the scope of the paper by Vastag (2000). Other researchers have suggested parametric methods, such as DEA, and non-parametric methods, such as the deterministic and stochastic frontier models, along with assigning proxy metrics for estimating firm performance frontiers (Coelli et al. 2005; Rosenzweig and Easton 2010; Clark 1996). However, Rosenzweig and Easton (2010) argue that an estimated positioning relative to an empirically derived frontier may not correspond to positioning relative to the actual frontier, and that it is difficult to evaluate the difference between the two. In addition, these methods are data intensive and difficult to execute in practice (Singh Srai et al. 2013), and as they originate in economic theory they are not designed, and therefore insufficient, to identify the root causes of productivity losses at an operational level (Czumanski and Lödding 2016; Klassen and Menor 2007).

Although several publications have tested and supported the propositions of Schmenner and Swink (1998) and Vastag (2000) concerning cumulative capabilities and tradeoffs, rarely has anyone attempted to graphically plot the asset and operating frontiers using empirical data. As of June 2016, the Web of Science database listed 242 articles citing Schmenner and Swink (1998) and 30 articles citing Vastag (2000). Of these, only the following authors present graphs including both asset and operating frontiers: Lapré and Scudder (2004), Cai and Yang (2014), and Singh Srai et al. (2013). Lapré and Scudder (2004) use the theory of performance frontiers to suggest how best to improve airline operations. Singh Srai et al. (2013) argue that they provide "the first comprehensive empirical validation of the integrated operations capability model where both asset and operating frontiers have been used," also in the airline industry. In these cases, the asset frontier corresponds to an airline's capacity to serve passengers, derived by multiplying the number of seats available in a flight by the distance over which the seats are flown. The operating frontier corresponds to the proportion of available seats actually occupied and utilized, representing the effective capacity of an airline. Cai and Yang (2014) are the only authors who plot both the asset and operating frontiers in a manufacturing context. They adopt a survey approach to explore the connections between business environments and firms' competitive priorities. They use three organizational characteristics as proxies for the asset frontier: investments in operation functions, number of employees, and firm profitability. Operation processes are seen as indicators of the operating frontier, using four items based on Malcolm Baldrige National Quality Award criteria to measure operation processes. Nevertheless, these items are not further specified and the publication from which they were adopted describes seven items (see Lau et al. (2004), which makes it difficult to establish how the operating frontier has been constructed.

Lastly, Rosenzweig and Easton (2010) and Sarmiento et al. (2008) advocate the use of longitudinal empirical data to monitor the development of capabilities and to enable firm performance comparisons based on the frontier approach. Their approach concerns internal aspects, i.e., changes in performance over time, and as well as external aspects, i.e., industry and competition levels. In addition, both argue that the detailed level of understanding required for such research may require case study methodology, which is supported by Boyer and Pagell (2000).

3 Methodology

This chapter describes how the research has been conducted by describing the research process in relation to the adopted view of science. The main research methods and techniques used are also presented.

3.1 Research approach

Research can be defined as an activity that contributes to the understanding of a phenomenon (Kuhn 1996). Selecting a research approach will indirectly determine what view of science is adopted, as the selection involves the role of theory and its relationship to research. As stated by Bacharach (1989), theory can be defined as a set of constructs and the relationships among them, along with boundary conditions, assumptions, and constraints. A theory should be parsimonious and describe or make predictions about the phenomena of interest. According to Wacker (1998), theory consists of four elements: conceptual definitions, domain limitations, relationship building, and predictions. As defined by Meredith (1993), in the normal research cycle, following an iterative process, descriptive models are expanded into explanatory frameworks, which are tested against reality until they eventually develop into theories. The initial conceptual models constitute sets of concepts, with or without propositions, used to represent an event, object, or process (Naumann 1986; Meredith 1993). Explanatory conceptual frameworks are collections of two or more interrelated propositions that explain an event, provide understanding, or suggest testable hypotheses. Finally, a theory corresponds to a group of interrelated concepts and propositions used as principles of explanation and understanding (Meredith 1993).

Two fundamental relationships between research and theory concern whether data are collected to test or build theories (Chalmers 1999; Popper 2002). When following a deductive strategy, the researcher uses existing theory to formulate hypotheses and thereafter collects data in an attempt to falsify the theory (Popper 2002). Conversely, when following an inductive strategy, the researcher uses observations and findings to build theories (Popper 2002). Quantitative research methods are typically related to a deductive strategy while qualitative research methods relate to an inductive strategy. However, the distinctions between the two strategies and their related methods are not as clear cut in practice as they are in formal definitions (Bryman and Bell 2007; MacCarthy et al. 2013). A selected research approach might include both inductive and deductive components in different parts of the research process. These two strategies should therefore be seen more as tendencies than as sharply distinguished entities (Bryman and Bell 2007).

3.1.1 Empirical model-based quantitative research

Meredith et al. (1989) have defined two dimensions of research approaches that shape the philosophical basis of research activities in OM: the rational/existential dimension and the natural/artificial dimension. The first dimension relates to the epistemological structure of the research process, i.e., the approach adopted to generate knowledge. The second dimension concerns the source and kind of information used in the research. In quantitative modeling, it is assumed that objective models can be built that can explain the behavior of real-life operational processes and capture related decision-making problems (Bertrand and Fransoo

2002). This is classified as a rational knowledge-generation approach by Bertrand and Fransoo (2002), using the terminology of Meredith et al. (1989). Moreover, Bertrand and Fransoo (2002) clearly distinguish between axiomatic quantitative modeling research and empirical quantitative modeling research. Axiomatic research is typically normative and tends to follow a deductive strategy (Bertrand and Fransoo 2002). It is therefore methodologically prescribed and uses formal methods from other branches, such as mathematics and statistics (Meredith et al. 1989). On the other hand, empirical model-based research is primarily descriptive and driven by empirical findings and measurements (Bertrand and Fransoo 2002; Filippini 1997).

The research presented here is positioned within empirical model-based quantitative research. A systems approach has been adopted to investigate the characteristics and behavior of production systems and their shop floor operations. As stated, a systems approach assumes that the reality or problem situation can be objectively modeled and is constructed of components that are mutually dependent (Von Bertalanffy 1972). In contrast to a strictly positivistic analytical approach, system components are not summative because they influence each other and create synergies (Von Bertalanffy 1972). Bertrand and Fransoo (2002) argue that because empirical model-based research is a rational and objective scientific approach, it requires systematic, objective, and situation-independent procedures when identifying and measuring real-life operational processes. This is referred to as the conceptual modeling of a system (Bertrand and Fransoo 2002; Mitroff et al. 1974), which is also often the initial step when conducting research, regardless of whether the research is descriptive, exploratory, or confirmatory (Meredith 1993).

Mitroff et al. (1974) have presented a generic approach to research methodology in OM, based on a systems view of problem solving (Figure 3.1). The conceptualization involves specification of the variables that will be used to define the nature of the problem to be studied. In the modeling step, the actual quantitative model is built by defining the significant relationships between the variables. Model solving involves the deduction of conclusions from the scientific model. Mitroff et al. (1974) claim that the actual research process can begin at any point in the diagram, further discussing the benefits or risks of choosing different paths. The complete research cycle, including all stages of the model (Figure 3.1), typifies empirical normative research. Such research largely incorporates research output from axiomatic descriptive research, which has developed paths for the modeling and model-solving stages (Bertrand and Fransoo 2002). Nevertheless, in developing the framework presented here, the selected methodological path is aligned with the “conceptualization–modeling–validation” cycle, which Bertrand and Fransoo (2002) claim is typical of empirical descriptive research. They further argue that validation is a core process in such research and acknowledge the related risk identified by Mitroff et al. (1974), namely, that researchers may be overly concerned with validation, attempting to achieve a perfect fit between model and reality.

The source and kind of information used are elaborated on in subsequent sections describing the research design and incorporated research and data-collection methods.

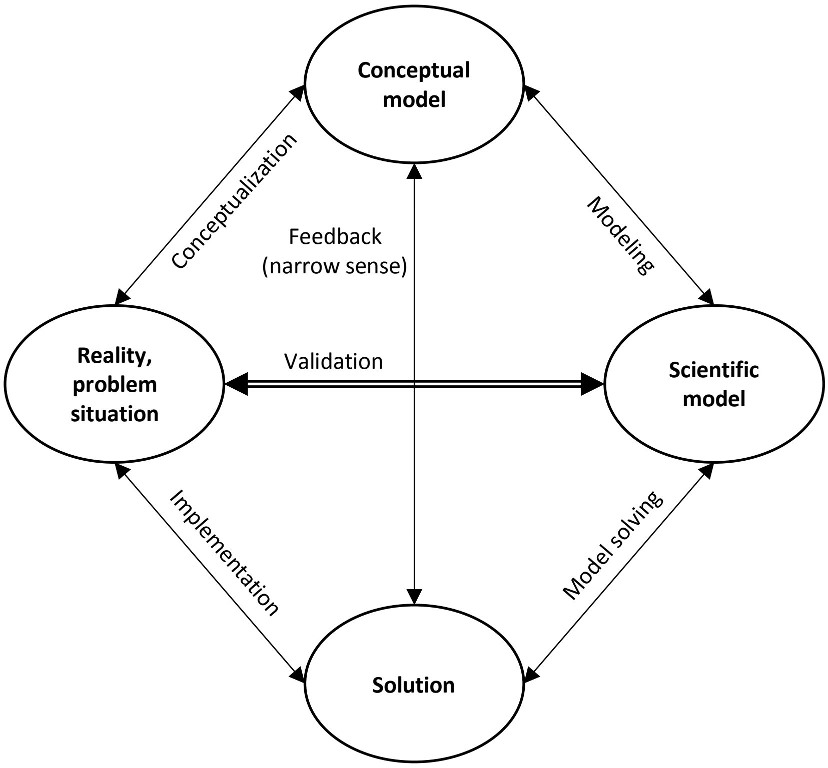

Figure 3.1. Research model of Mitroff et al. (1974).

3.2 Research design

The research presented here was conducted from 2011 to 2015 and involves case studies, the secondary analysis of datasets, and one survey. In total, five empirical studies referred to as Studies 0, I, II, III, and IV were performed. They are arranged chronologically in the research timeline in Figure 3.2. Study 0 corresponds to the Chalmers Electronics Production (ChePro) project funded by the Swedish Foundation for Strategic Research (SSF) and the ProViking 2 research program. It began two years before the employment of the author, while the remaining studies (I–IV) were initiated and designed by the author. A description follows of the characteristics of the research methods used, how they relate to the empirical studies, and their association with the appended papers.

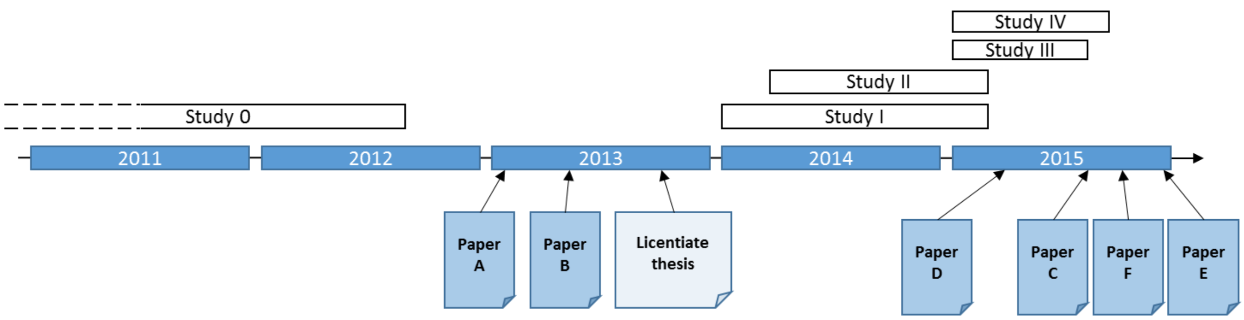

Figure 3.2. Research timeline.

3.2.1 Case study

The use of case studies is well established in the OM community (Voss et al. 2002; Flynn et al. 1990) and has proven particularly suitable when it comes to studying phenomena in their natural settings (Eisenhardt and Graebner 2007). Case studies can be designed to have different emphases depending on the research purpose. This means that they can be used for theory building and theory testing, as well as theory elaboration (Voss et al. 2002; Ketokivi and Choi 2014). Early in research projects, case studies are often employed to uncover areas for research and theory development (Voss et al. 2002). Case studies constitute the research design used in Studies 0, I, and II.

In Study 0, five case studies were performed, structured as multi-site case studies with a theory-building emphasis. These studies took place in the Swedish electronics manufacturing industry. The case companies were selected based on their participation in the ChePro project. Four of the five case companies are categorized as small and medium-sized enterprises (SMEs) with 50–250 employees, and one is considered a large company. The author participated in gathering and analyzing the empirical data in three of the five case studies and co-authored the paper describing the findings, i.e., Sundkvist et al. (2012). For the purpose of this research, the units of analysis were the identified key constructs needed to describe the operational improvement potential of a production system, thereby primarily addressing RQ1. Consequently, findings from Study 0 correspond to the formulation of the reality and problem situation underlying the subsequent conceptualization and modeling activities. These activities resulted in a production system model presented in Papers A and B, in which the development of the modeling approach constituted the research presented in the author's Licentiate thesis (Hedman 2013). The production system model has also been incorporated into a framework that explains how shop floor productivity improvements can provide financial benefits (Sundkvist 2014) and implemented in a software prototype as part of a Bachelor's thesis (Bengtsson et al. 2014) supervised by the author.

The case studies of Studies I and II were structured as single-case studies and primarily conducted as part of the process of validating the proposed framework. They emphasized theory elaboration and therefore follow a logic similar to that of theory testing, though the empirical findings are not anticipated by the a priori formulation of propositions (Ketokivi and Choi 2014). In this type of case research, a general theory that can be used to approach the empirical context is identified and the actual elaboration involves concepts and combinations from several theories (Ketokivi and Choi 2014). The theory of performance frontiers (Schmenner and Swink 1998; Vastag 2000) had previously been identified by Sundkvist (2014) as the general theory on which the theory extension efforts would be based. In both studies, the units of analysis were the case companies' production systems and associated operational processes. The studies aimed to contribute primarily to RQ3 in how the operational improvement potential can be captured to support decisions about improvement initiatives, but as it covers the application of the model from Papers A and B it also contributes to RQ 1 and 2.

The case company in Study I is a medium-sized electronics manufacturer selected based on two criteria: the operational characteristics of automated production and ongoing operational improvement initiatives. An initial study was conducted to establish a current-state description of the system. This involved direct measurements at an operational level using work study techniques such as work sampling. These measurements were made as part of a Master's thesis project (Bergström and Plamkvist 2014) supervised by the author. Raw data from the direct measurements were modeled, further analyzed, and incorporated into the proposed framework by the author. Supplementary unstructured interviews with production managers and onsite visits were conducted by the author. After one year, a followup study was conducted by the author by means of structured interviews and the acquisition of historical production data.

In Study II, the case company is a large-sized engine manufacturer selected based on two criteria: the operational characteristics of manual assembly and the company’s novel system for automatic data acquisition developed specifically for manual assembly. A separate analysis of this system and its data acquisition capabilities was performed structured as a best-in-class case study. The findings are presented in Paper D and the process of validation, based on Studies I and II, is presented in Paper C. Study II was designed by the author, who also performed all the data collection and analysis.

3.2.2 Secondary analysis

Secondary analysis is defined by Bryman and Bell (2007) as the analysis of data that the researcher has not participated in collecting, which could be data collected by organizations or other researchers as well as official statistics. Bryman and Bell (2007) claim that a main benefit of using secondary data is the opportunity to employ large datasets based on large samples, while a typical limitation is the lack of control over data quality. The secondary analysis of datasets was conducted in Study III and in parts of Study IV.

Study III was based on a large dataset of production-followup data from 23 companies and 884 machines covering six months of production. The dataset was provided by Good Solutions AB, an industrial software company specializing in real-time production followup and disturbance management. The study was initiated and designed by the author and the data modeling was performed as part of a Master’s thesis project (Subramaniyan 2015) supervised by the author. Furthermore, the study aimed to identify critical factors when using automatic data-acquisition systems to measure equipment efficiency. It also involved an analysis of the extent to which operators can affect OEE. The author was responsible for the analysis and classification of 499 unique stop categories. The findings of Study III contribute mainly to RQ1 and RQ3 and are presented in Paper E.

The secondary analysis in Study IV was based on official statistics regarding the capacity utilization of Swedish industry. The author acquired raw data from Statistics Sweden’s business tendency survey, and the resulting large dataset contained reported capacity utilization rates from 2005 to 2008. In total there were 28,943 cases, each corresponding to one company and its reported capacity utilization rate. The data were sorted and categorized using the Swedish Industrial Classification (SNI) standard. Study IV was initiated to obtain a national overview on the operational improvement potential in production systems. It is therefore not directly related to the development of the proposed framework, though it contributes directly to RQ3; the findings are presented in Paper F.

3.2.3 Survey

The survey is the most common quantitative research method used in OM (Flynn et al. 1990; Taylor and Taylor 2009). A survey was performed as part of Study IV. The purpose was to explore the extent to which respondents to Statistics Sweden's business tendency survey consider capacity-influencing factors when reporting capacity utilization rates. The population consisted of Swedish manufacturing companies belonging to the same industry groups as those in the secondary analysis of the official statistics. This corresponded to 998 companies, according to the Retriever business database. A sample of 244 randomly selected companies was contacted by telephone. Complete responses were obtained from 105 companies, corresponding to a response rate of 43.0%. Using telephone interviews as a survey method is beneficial as it allows the control of question order, the wide geographic distribution of the sample, and a fairly low risk of response bias (Blair et al. 2013). However, it also requires that the questions be made short and simple. In addition, it is difficult to get information about refusals and non-contacts (Blair et al. 2013). The major challenge of this survey was to contact the right person at each company. As a result, the most common reason for non-response was that the requested person could not be reached. A test of non-response bias was nevertheless conducted, and chi-square statistics revealed no significant differences at the $p < 0.05$ level between respondents and non-respondents regarding industry group and company size. The results of the survey are presented in Paper F.

3.3 Contribution to research questions

An overview of how the empirical studies and appended papers address the research questions is depicted in Figure 3.3. In summary, the two initial papers (A and B) present the conceptual production system model that is central to the framework for identifying and objectively measuring the relevant characteristics of real-life operational processes. This framework and the underlying model are empirically validated in Paper C. Paper D covers some of the practical issues concerning how the operational improvement potential can be captured and proposes a holistic approach for doing this. Paper E emphasizes the key constructs of automatic activities and how they relate to capturing the operational improvement potential of automated processes. Paper F identifies how the ambiguity of and different perspectives on the capacity concept have resulted in a misleading view of the manufacturing industry at a national level, where the operational improvement potential is obviously neglected.

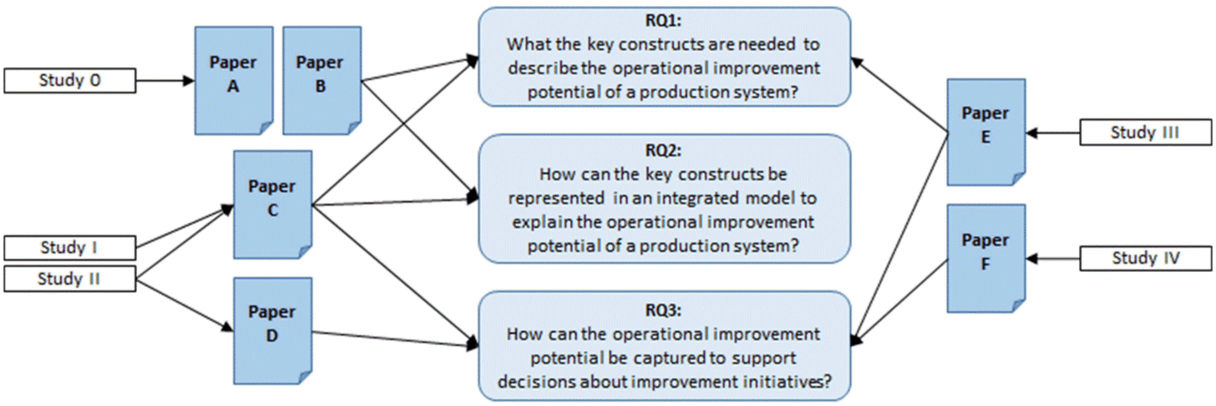

Figure 3.3. Relationships between the studies, appended papers, and research questions.

4 Results

This chapter summarizes the results of the appended papers. The focus is on the contributions of each paper to answering the research questions.

4.1 Papers A and B

Title (Paper A): Object-oriented modeling of manufacturing resources using work study inputs

Title (Paper B): Reference model of manufacturing resources

A reductionist viewpoint was adopted when developing the production system model presented in Papers A and B. This means that efforts were made to reduce the production system complexity to a manageable level by concentrating on the specific relationships between the identified constructs that describe the operational improvement potential. These constructs and their relationships were, as stated, primarily formulated based on the findings of Study 0 and on the body of industrial engineering knowledge. Paper A describes the first version of the model and proposes how input from work measurement techniques can be used to describe the characteristics of the model's entities. Paper B builds on this and extends the model description into a reference model to be operationalized in software for rapid scenario analyses or to provide input data to more advanced simulation tools. Both papers emphasize manual operations.

4.1.1 Production system model

The three fundamental entities of the model are "Manufacturing resource," "Activity," and "Facility" (Figure 4.1). The definition of "Manufacturing resource" was adopted from ISO 15531 MANDATE, which states that a manufacturing resource is "any device, tool, and means, except raw material and final product components, at the disposal of the enterprise to produce goods or services." Therefore, "Manufacturing resource" has two subclasses, "Equipment" and "Human," that inherit its properties. As seen in Figure 4.1, there are two different hierarchies in the model: the compositions of "Activity" and "Facility."

"Activity" comprises one or several "Sub-activities' that in turn comprise one or several "Elements." The elements correspond to basic movements, as defined in a predetermined time system. As each element therefore has a defined standard time, the target time duration of the activity equals the sum of its ingoing elements. A "Production process" is defined as a "structured set of activities or operations performed upon material to convert it from the raw material or a semi-finished state to a state of further completion" (ISO 2005). Analogously, the target time duration of a production process equals the sum of its ingoing activities. A production process equals an operational process. To avoid ambiguity, the summaries of remaining appended papers will henceforth refer to production processes as operational processes, even though this term was not used in Paper A or B.

The "Facility" entity represents defined areas in a production system. As presented below, it is hierarchal, composed of the entities "Factory," "Subsystem," and "Workstation." Subsystems are defined areas in a factory (i.e., departments) and a subsystem consists of one or several workstations, which, in turn, are defined areas in the subsystem. These facility levels are incorporated to define system boundaries when capturing and assessing the operational improvement potential of an operational process. An operational process can thus be seen as the entire process of converting raw material to finished products (i.e., the Factory view) or as a delimited set of activities performed in a "Subsystem" or at a "Workstation." Production systems are open systems, so the delimited part of the production system will be affected by the surrounding environment, such as other subsystems, regardless of any system boundaries. However, by defining a system boundary, it is possible to isolate what effects can be related to the delimited system and what effects result from interdependencies with the environment.

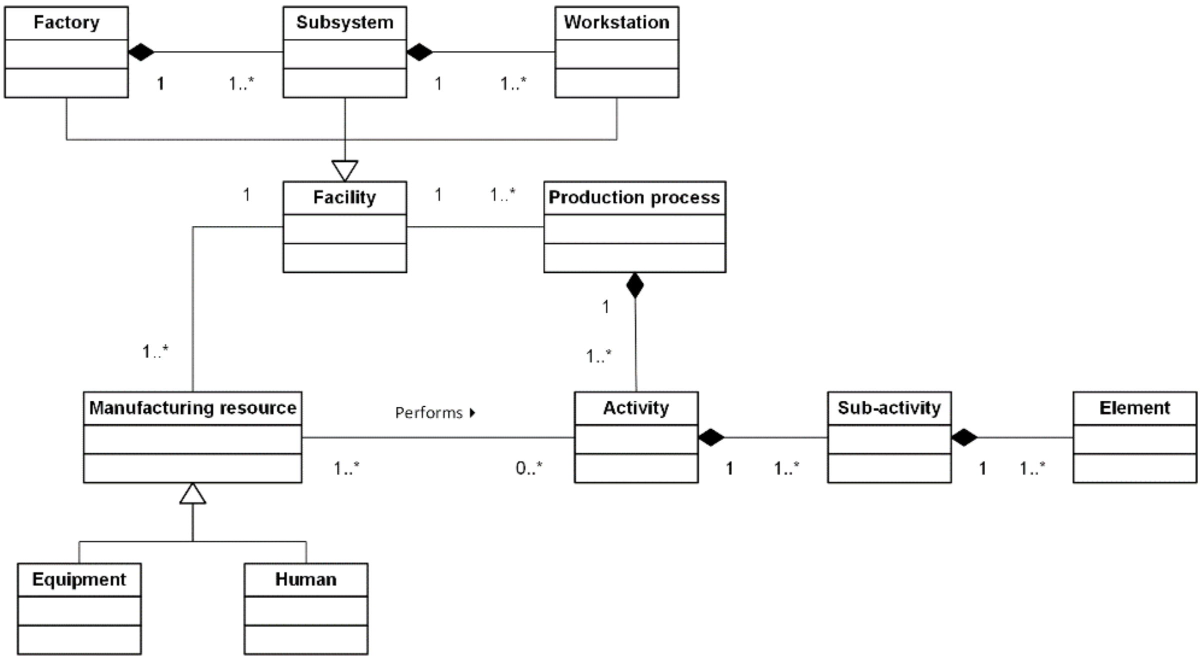

Figure 4.1. Production system model (Paper A).

4.1.2 Resource characteristics

Adopting the ISO 15531 MANDATE definition, manufacturing resources are described based on four characteristics: "administration," "capability," "constitution," and "capacity" (Figure 4.2). "Capability" is the characteristic that describes manufacturing resources' ability to perform shop floor activities relative to a defined standard time: for manual activities, that capability is related to skill and physical ability; for automatic activities, it is determined by the physical condition and operating status of the equipment and also by the skill of the operator handling the equipment. "Administration" concerns the identification of a resource. "Capacity" describes the potential workload of the resource, expressed as the available capacity that can be allocated as planned production time. Finally, "constitution" is not applicable to humans because it primarily concerns equipment-related attributes such as functions, tolerances, and technical specifications.

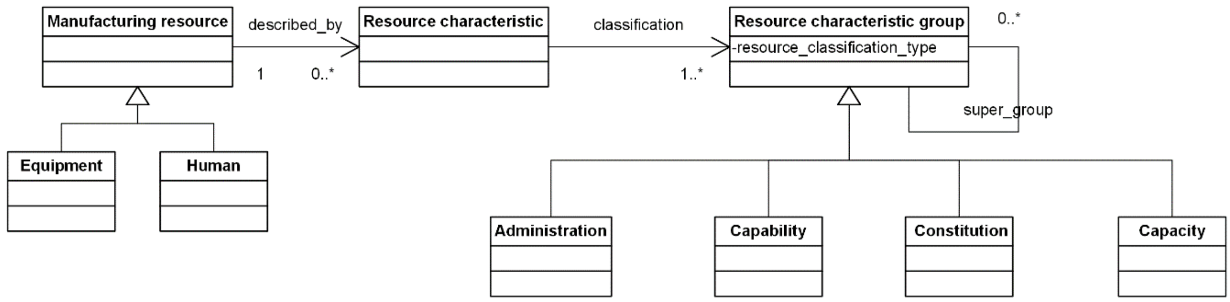

Figure 4.2. Manufacturing resource characteristics (Paper B).

4.2 Paper C

Title: Capacity frontiers: Capturing the operational improvement potential of production systems

The purpose of this paper was to present an approach based on the theory of performance frontiers for capturing and assessing the operational improvement potential of production systems. It also presents a proposed framework that can be used for identifying and objectively measuring the characteristics of operational processes, referred to as the capacity frontier framework.

4.2.1 Key points of the capacity frontier framework

A capacity frontier is defined as the maximum throughput rate of a production process, given the design of its operations and the capabilities of assigned resources. There are two distinct types of capacity frontiers: ideal capacity and real capacity frontiers. The ideal capacity frontier represents the composition of a process's ingoing activities and, consequently, the current standard for how activities are planned or intended to be performed. It is derived by inverting the target cycle time of the bottleneck activity and corresponds to the ideal productivity rate of the process. The real capacity frontier equals the actual throughput rate of a process in a defined period. Consequently, the relationship between the two frontiers is a measure of capacity utilization.

There are two primary approaches to improving an operational process, i.e., increasing its ideal capacity or increasing its real capacity. The ideal capacity can be increased through investments in new equipment or changing the production system layout. It also involves improving the planning and design of shop floor activities, thereby improving the current standard. The real capacity can be increased by capturing and reducing production system losses or by improving the capabilities of resources. The operational improvement potential should only be assessed in relation to planned capacity, which corresponds to planned production time. Two categories of losses are defined in the framework: performance losses and utilization losses. Performance losses, as defined in Table 4.1, are directly associated with the resource characteristic "capability," which is related to skill and physical ability. Utilization losses are classified according to the variables in Table 4.2 and are intended to capture system losses caused by outages related to production system design, disturbances, and policy decisions.

Table 4.1. Performance factors (Paper C)

Variable	Description
Personal performance rate (P_P)	Determined by the individual's physical ability and his or her motivation to perform activities relative to the standard time.
Skill-based performance rate (P_S)	Determined by the individual's previous training and experience, which affect his or her ability to perform specific activities relative to the standard time.
Equipment performance rate (P_E)	Determined by the operating status (condition) of the equipment. In addition, it is affected by the operator's ability to operate the equipment according to the defined speed standard.

Table 4.2. Utilization factors (Paper C)

Variable	Description: Human	Description: Equipment
Need-based utilization rate (U_N)	Defined as lost production time, which is determined by the need for relaxation and personal time. It is often regulated by agreements at the workplace. It includes paid breaks and losses before and after breaks.	Defined as lost production time when equipment is idle due to preventive maintenance and tool changes during planned production time.
System-designed utilization rate (U_S)	Defined as operator idle time caused by non-preemptive outages. Typically includes balancing losses found on assembly lines and at semi-automated workstations; it also includes material shortage.	Defined as equipment idle time caused by non-preemptive outages such as balancing losses (i.e., blocking or starvation) and idle time during setups. It also includes idle time during operator meetings, breaks, and shift changes if they occur during planned production time.
Disturbance-affected utilization rate (U_D)	Defined as lost production time caused by preemptive outages. It includes the time from discovery of the disturbance until the work is performed at full speed again.	Defined as equipment idle time caused by preemptive outages. It also includes running time when the equipment is producing defective units (if applicable).

The capacity frontiers and the operational improvement potential are visualized in a diagram (Figure 4.3). This is a redesign of the extended performance frontier diagram in which the horizontal axis represents time instead of a set of inputs and the vertical axis represents manufacturing performance defined as the throughput rate of a process. The frontiers are constructed bottom–up starting from the workstation level. Aggregation is conducted according to the facility hierarchy of the production system model (Papers A and B) and follows a constraint-based approach: the ideal capacity frontier at a workstation level is determined by the constraining activity, the ideal capacity frontier at a subsystem level is determined by its constraining workstation, and so forth. Performance and utilization losses are measured at each facility level depending on the required, or feasible, level of detail. Independent of the type of loss, the common measurement unit is always time or, more specifically, lost time. Performance and utilization losses can be distinguished when the actual time duration exceeds the target cycle time.

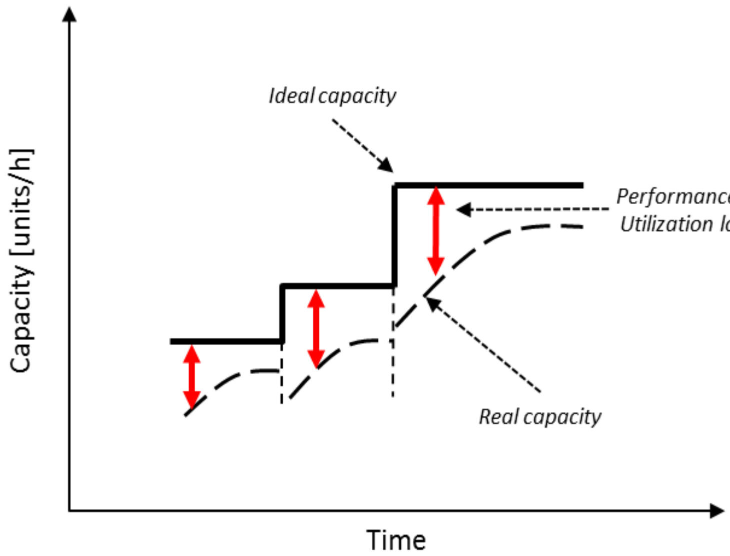

Figure 4.3. Conceptual capacity frontier diagram (Paper C).

4.2.2 Implications of Studies I and II

Unlike more aggregate approaches, the capacity frontier framework can be used to capture the operational improvement potential. It provides a deeper understanding of the underlying reasons why some firms are more productive than others and of the types of operational improvements that should be prioritized to improve productivity and increase capacity. The capacity frontiers were determined and the corresponding diagrams constructed based on the results of Studies I and II. In Study I, the findings were used to evaluate and benchmark the differing improvement potentials of two operational processes performed in the same subsystem. Study II illustrated how the framework can be applied to increase the capacity of an automated process by focusing on equipment losses as well as operator losses and their interdependencies. Both studies revealed how the validity of the standard, i.e., the ideal capacity frontiers, directly affects how well the operational improvement potential can be captured and evaluated.

4.3 Paper D

Title: A state of the art system for managing time data in manual assembly

This paper addresses the practical issues encountered in capturing the operational improvement potential of a production system through using an automatic data-acquisition system, with an emphasis on manual operations. Focusing specifically on the quality of operation times, its purpose was to demonstrate how accurate operation times can be confirmed and sustained. Previous research has demonstrated that many companies do not update the operation times in their planning systems. This results in an accumulation of allowances, with the gap between planned and actual operation times continually increasing and the operational improvement potential remaining hidden. Inaccurate time data at the operational level have negative synergies all the way to the strategic levels of an enterprise and can negatively affect decisions related to investments, price setting, and customer offers. At the tactical level, inaccurate operation times will lead to operational inefficiencies: for example, production planners will have extra work when they are forced to make adjustments to compensate for inaccurate operation times, and any detailed planning or optimization also becomes unattainable.

In Study II the system was evaluated in relation to the processes of time data management (TDM), which had been derived from a state of the art TDM morphology. The system integrated two functions, i.e., process planning and design and production follow-up, involving the primary stakeholders of operation times: process planners, operators, and managers responsible for production planning and control. The system enabled seamless integration, so that if process planners changed an operation time, it was automatically updated for the remaining stakeholders. In principle, process planners update the operation times every time there is a process change (≈150 per year) or change in product design (≈200 per year). Operation times are determined using the predetermined time system MTM-SAM. Operators provide continuous feedback on the quality of the time data and the performance of the operational process by digitally reporting deviations at a workstation level. Production control collects the follow-up data and initiates improvement initiatives through the maintenance function when needed. They also use the updated operation times to make order plans that are communicated to the process planners. However, evaluation results indicated that the company operating the system did not exploit its full potential. This primarily concerned the administration of follow-up data and disturbance management as well as the misinterpretation of predefined loss categories.

Nevertheless, the identified technical potential of the system constitutes the basis for a holistic view of the lifecycle of operation times, shown in Figure 4.4, which confirms and sustains updates the quality of operation times. This view integrates the three primary functions centered on the manual assembly activities. Standards should be developed from the determined time data based on the work content of the manual assembly activities. The "standards loop" represents the process of continuously evaluating the standards so that their duration and work content conform to the actual operations that they represent, which requires continuous feedback from the shop floor. An incorrectly set time standard will directly affect the quality of the output of process planning. This can force operators to work beyond their capabilities, in terms of performance, or result in inefficiencies being built into the operational process. In both cases, this will prevent the sustainable use of manufacturing resources.

The performance of operational processes and, consequently, the results of production control policies are evaluated by production planning and control in the "planning loop." This is accomplished by comparing the actual versus planned outcome of a process measured as either output, such as produced units, or duration. Operational process performance is influenced by the capabilities of assigned resources and the disturbances in the system. Identifying the operational improvement potential requires that the process performance be evaluated relative to valid time standards and that disturbances and deviations be captured.

As continuously evaluating both standards and operational process performance will facilitate the identification of operational improvement potentials, there is also a need to systematically manage improvement initiatives. In the "improvement loop," initiatives should be prioritized and directed to focus either on standards, through improving methods or investing in new equipment, or on reducing disturbances and improving the abilities of resources to reach existing standards.

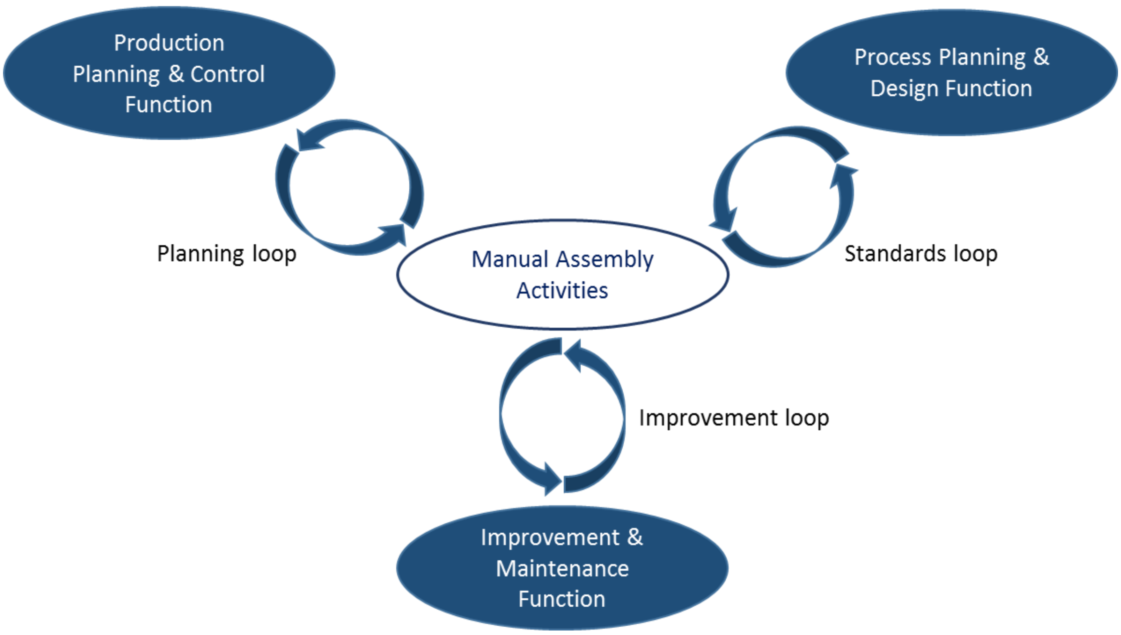

Figure 4.4. The lifecycle approach to operation times (Paper D).

4.4 Paper E

Title: Analysis of critical factors for automatic measurement of OEE

The automatic measurement of OEE is a primary reason why companies invest in manufacturing execution systems. The purpose of this paper is to identify the critical factors and potential pitfalls when operating systems for the automatic measurement of OEE. The paper concentrates on the key constructs of automatic activities, the relationship between equipment and operators, and how that relationship affects equipment efficiency. The extent to which OEE measures the operational improvement potential is determined by companies' data collection ability and accuracy in doing so. Before Study III, it had already been recognized that varied interpretations of the underlying loss factors of OEE constitute a common reason for variation between companies.

Study III aggregated the OEE measures calculated for four industry groups (Figure 4.5), and the results indicated that the overall median OEE of all 23 companies is 70%, whereas the average OEE is 65%. It was impossible to determine whether or not the individual equipment constituted bottleneck machines. Nevertheless, the data were cleaned by excluding planned downtime losses so that the calculated OEE measures represent the equipment efficiency relative to planned production time. It was also found that 702 out of 884 machines (80%) had a recorded performance rate of 100% and that 796 out of 884 machines (90%) had a recorded quality rate of 100%. It was concluded that such a large proportion of machines is unlikely to be operating at full efficiency. This conclusion was supported by the fact that “100%” constitutes the default value for speed and quality efficiency in the measurement system. Moreover, previous research also revealed that many companies do not measure cycle times or have sufficient knowledge of the theoretical maximum performance, which is required to determine speed efficiency. This implies that most calculated OEE values measure availability rather than *overall* equipment effectiveness.

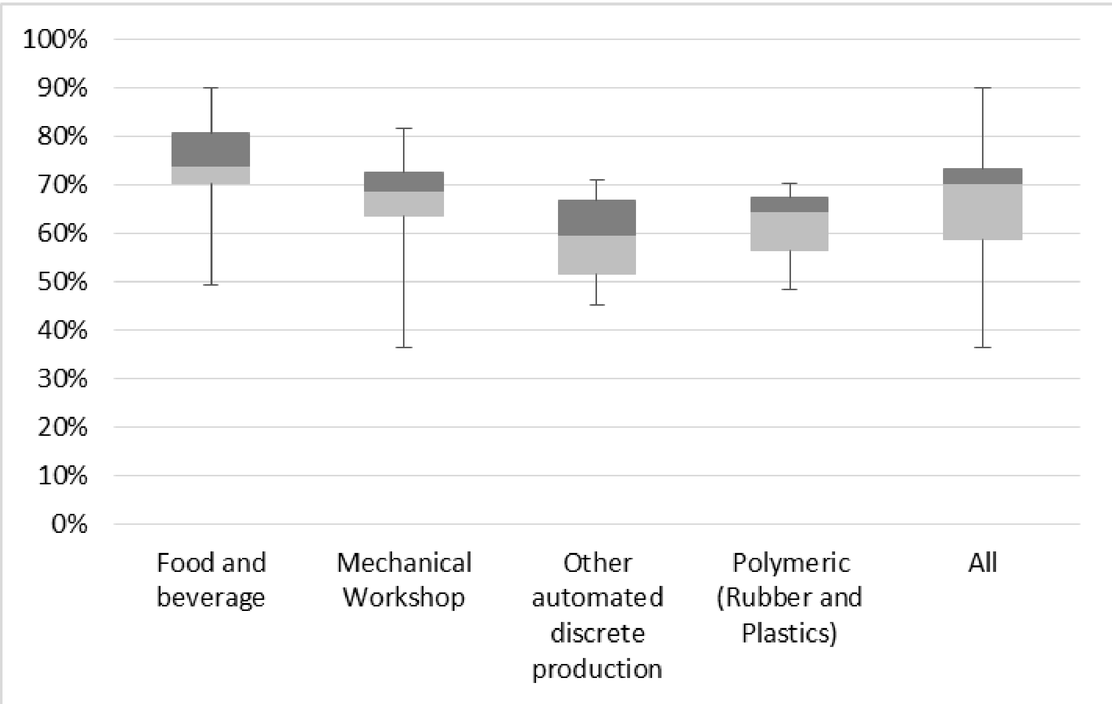

Figure 4.5. OEE comparison of industry groups (Paper E).

The distribution of recorded loss times is shown in Figure 4.6, where it can be seen that unclassified losses represent approximately 19% of the scheduled production time for all machines. This corresponds to more than half of all recorded loss time and negatively influences the applicability of the data for directing improvement initiatives. The operational improvement potential cannot be considered captured if the causes of losses are not communicated to those responsible for prioritizing and investing in improvement initiatives.

In addition, the losses that could be classified were categorized in relation to the extent to which the loss is operator influenced based on the following definitions:

- **Operator-influenced loss time** is loss in which the duration of downtime, from when a failure occurs until the point when the equipment returns to operation, is dependent on the activities carried out by operators (i.e., detection and repair). This also includes manual activities performed during equipment idle time, such as changeovers, measurements, and adjustments.
- **May be operator influenced loss time;** is loss in which the duration of downtime may be dependent on the activities performed by operators. It primarily concerns categories related to material shortage and waiting time. In such cases, it is impossible to determine whether the equipment is idle waiting for an operator to attend (i.e., refill material or attend the blocking/starvation of the machine) or whether the idle time is more influenced by factors other than the operator, for example, caused by an overall lack of material in the inventory or balancing losses due to production system design.
- **Not operator-influenced loss time** is loss in which the duration of downtime is independent of operator activities, for example, due to lack of material from supplier and external deliveries.

As seen in Figure 4.6, approximately 90% of the recorded classifiable downtime was directly related to supporting activities performed by operators and not to the automatic process itself. This reflects the complex interdependencies between individual equipment and the surrounding environment, where the internal efficiency of the equipment largely depends on operator actions and on companies' production and control policies.

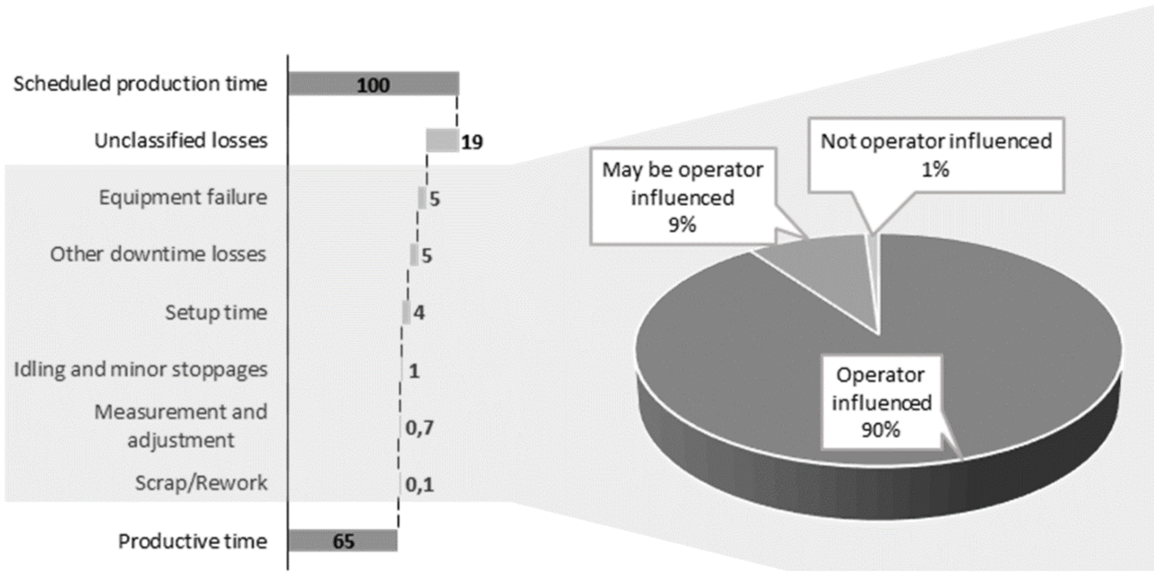

Figure 4.6. Classification of loss time by levels of operator influence (Paper E).

4.5 Paper F

Title: On the measurement of capacity utilization in industry: A critical reflection from a shop floor perspective

This paper represents the beginning and end of the performed research. Chronologically, it was among the last parts of the research to be written up, but it emphasizes a main motive for initiating the PPA studies, which subsequently motivated the performance of the research presented here.

Capacity utilization in industry is an economic indicator employed by policymakers and central banks for analyzing and predicting business cycle fluctuations. It constitutes the basis for formulating monetary policies that affect the investment behavior of companies. The statistics were collected at a plant level through business tendency surveys in order to reflect how much of a plant's production capability is being utilized. The results are also communicated to the daily press and reach stock traders as well as enterprise managers. This paper focuses specifically on the business tendency survey administered by the governmental agency Statistics Sweden. The respondent companies are required by law to report their capacity utilization for the last quarter, defined as:

> … the ratio between actual production and full production capacity, where actual production corresponds to the degree to which the industrial organization's machinery has been utilized during the current working schedule for the latest quarter, and full production capacity refers to the maximum level of production that is reachable with the existing machinery and current working schedule.

In the first part of Study IV, raw data from the business tendency survey were acquired. They were sorted and categorized to include companies from the industry groups that participated in the PPA studies during the 2005–2008 period. For that period, it was found that in over 38% of the 7441 cases the capacity utilization rate was reportedly 100% or more. This contradicted the findings of the PPA studies, which indicated that the average utilization of bottleneck machines was 62% and that, in general, companies had considerable potential to increase the utilization of existing resources.

In the second part of Study IV, the respondents to Statistics Sweden's business tendency survey were contacted to explore how well the survey captures the practical reality in factories. It was found that over half the sampled companies neglected principal factors affecting capacity utilization derived from a review of the engineering and industrial organizational literature. Moreover, the results indicated that there was no consensus on how to measure capacity and that the individuals responsible for reporting capacity utilization, with few exceptions, worked in the accounting departments of the companies and had little knowledge of manufacturing system characteristics. As the definition of capacity utilization used in the survey directly implies that the internal efficiency of production systems is being captured, the criticism of the capacity utilization measure was twofold:

1. Companies that do not consider the principal influencing factors of product mix, scrap rate, and production disturbances are not reporting a capacity utilization that represents the practical reality in factories.
2. Companies that report a capacity utilization of 100% (or more), by definition, are not reporting a capacity utilization that represents the internal efficiency of their plants.

Based on the findings of this paper, it can be argued that a misleading view of industry is conveyed by the reported capacity utilization statistics. Recommendations were made for a redesigned business tendency survey that more clearly distinguishes between plant-internal and plant-external influencing factors. It was also proposed that cumulative measures of downtime and scrap should be collected and included in the analysis of the current state of the manufacturing industry, an analysis that would be based on a more holistic view of plant-level capacity utilization.

5 Discussion

This chapter discusses how the main results relate to the research questions and the objective of the thesis. This is followed by discussion of the academic contribution and industrial relevance of this research.

5.1 Answering the research questions

The following sections' answers to the research questions are intended to fulfill the stated purpose of advancing our understanding of the improvement potential of real operational processes.

5.1.1 What key constructs are needed to describe the operational improvement potential of a production system?

In the most abstract sense, constructs are the building blocks of theories that are used to explain phenomena and correspond to the conceptual vocabulary of a domain. Variables are used to operationalize and measure the constructs, each of which can be represented by several variables.

Paper C presented how the operational improvement potential of a production system is evaluated based on its intended versus actual state. The intended state is operationalized as the ideal capacity of a production system's operational processes. It is classified and measured using the composition of activities presented in the production system model in Papers A and B. The potential to improve the ideal capacity can be identified from the lowest level by eliminating unnecessary movements (elements) to higher-level improvements, such as redesigning the production system layout or acquiring new equipment and tools. This is also referred to as the method potential, using the vocabulary of Helmrich (2003) and Saito (2001). It is clearly stated that the ideal capacity should not be interpreted as being the same as the optimal capacity. As the ideal capacity should be defined based on how the ingoing activities are to be performed, it corresponds to the current standard. If a standard has been formulated accurately, it should be possible to distinguish what constitutes the norm time duration of the activities from the time elements added as allowances (Niebel and Freivalds 2003), as in the case presented in Study II (Paper C). The formulated standard should therefore be based on the skill- and physical-ability-related capabilities of the resources that are to perform the activities. The standard for automatic activities should be formulated based on the theoretical maximum performance of the equipment. It will otherwise be impossible to capture any improvement potential related to its speed efficiency, as seen in Paper E. Consequently, if a standard is missing or poorly defined, the method potential part of the operational improvement potential cannot be described and it becomes significantly more difficult to align production control polices with the capabilities of resources. It also becomes difficult to distinguish between increased production and increased productivity.

While the ideal state of a production system exists only on paper, the construct's real state is a direct result of how well resources are able to perform planned activities. The construct's real state is operationalized as the real capacity of a production system's operational processes and measured as the actual output of a process given a defined period. However, to explain the real capacity and how it potentially differs from the ideal capacity, the losses and synergies that occur when resources perform activities must be captured. This can be done at different levels of detail depending on the degree of accuracy that is required or feasible. These levels correspond to the facility hierarchy of the production system model. Paper C illustrates how the losses and, consequently, the operational improvement potential of the real capacity are captured by measuring performance and utilization losses using their defined variables.

5.1.2 How can the key constructs be represented in an integrated model to explain the operational improvement potential of a production system?

The production system model (Papers A and B) illustrates how the key constructs are integrated to describe the operational improvement potential of a production system. Paper C provides a more comprehensive picture of the interdependencies between model components based on the empirical data from Studies I and II. Reductionism and holism were incorporated as complementary strategies because the model was developed following a reductionist approach, while the resulting model incorporated in the framework (Paper C) was intended to contribute to advance our understanding of the improvement potential of a production system as a whole. As a result, the object-oriented design of the model arranges the data so that it is possible to zoom in on different levels using the facility hierarchy or activity composition to investigate the details of the system. Zooming out results in an ability to distinguish the emergent properties of the system as a whole, facilitating examination of the external structure of the system. Visualization of the characteristics and constitution of the shop floor productivity losses is enabled, even at aggregated levels.

As production systems are open systems, the system boundary, defined using the facility hierarchy of the model, cannot stop the system from interacting with its environment. It is nevertheless possible to distinguish between losses caused by surrounding system effects and internal causes that can be isolated. Paper C presents how this constitutes the fundamental distinction between performance losses and utilization losses, which have been elaborated based on the original definitions presented by Helmrich (2003) and Saito (2001). Performance losses are directly associated with the capabilities of individual resources and can therefore be isolated. Utilization losses, on the other hand, are affected by disturbances from both inside and outside a system boundary.

The production system model is conceptual and can describe the relationships between resources, activities, and their properties. However, the formal, or scientific, model derived from the modeling process must be incorporated in order to explain the phenomenon and how it occurs. This can be seen in Paper C, which introduces the capacity frontier framework, demonstrating how to explain and evaluate the effects of the interactions between resources, activities, and surrounding system effects.

Finally, even though the adopted definitions of manufacturing resources and the structure of the resource characteristics are formulated in EXPRESS, the model is expressed using UML. Nothing prevents the model from incorporating EXPRESS or any other similar modeling language, but UML was chosen to facilitate software implementation, which was a primary focus of the initial part of the research process.

5.1.3 How can the operational improvement potential be captured to support decisions about improvement initiatives?

This research question was formulated to ensure that the operational improvement potential is not neglected when strategic decisions are made. Based on the findings presented here, the operational improvement potential of a production system is arguably derived by assessing its capacity utilization.

Operational improvement potentials are realized through improvement initiatives, which in turn correspond to investments. The magnitude of an improvement initiative can range from minor investments, for example, in new tools and other aids, to large investments involving, for example, education and training programs, new equipment, and new production system design. In general, decisions concerning smaller investments are not made at a strategic level. However, the underlying rationale for assessing internal capacity utilization from a bottom–up perspective is that many small productivity improvements could potentially lead to a large increase in capacity. Neglecting them will obstruct companies from improving their existing operations before considering larger investments in new equipment or other assets and will, consequently, not contribute to the sustainable utilization of existing resources.

Decision-makers at a strategic level are likely not interested in the method improvement potential of the individual operations or various performance and utilization losses found in particular subsystems. However, they are interested in what their plant can produce relative to what it is actually producing. This information is depicted using capacity frontier diagrams, as seen in Paper C. For decision-makers, the diagrams indicate whether efforts should be directed to align the ideal capacity to meet the requested capacity (i.e., what is requested by the customer) or to increase the real capacity by reducing slack to its ideal capacity frontier. In terms of improvement initiatives intended to increase capacity, this translates into decisions as to whether investments are to be made in fixed assets and production system design (i.e., improving the ideal capacity frontier) or in operation improvements through, for example, workforce training and reducing productivity losses (i.e., improving the real capacity frontier).

When assessing the capacity utilization of a plant, the capacity frontier framework first depicts the capacity utilization of the plant's production system and the internal efficiency of the plant. The aggregation strata of the capacity frontier framework enable the visualization of detailed productivity losses from the workstation level to the factory level. In theory, this logic is straightforward; however, the empirical findings presented here identify several practical challenges:

First, to capture the full operational improvement potential, the standard must be accurately defined, as discussed in the answer to RQ1. Paper D demonstrates, in practice, how a valid time standard for manual operations can be determined and sustained by using the holistic life cycle approach to operation times. However, previous research has demonstrated that this is often neglected by both practitioners and academics (Kuhlang et al. 2014; Almström and Winroth

2010). This is also aligned with the findings of Paper E concerning automated processes, which imply that many companies do not measure cycle times or have insufficient knowledge of the theoretical maximum performance of their equipment resources. Compared with manual operations, standards for automatic activities should be more easily formulated through the use of process-planning software or the like. However, the standard and, consequently, the ideal capacity of an automated process also involves the management of supporting manual operations that significantly influence the overall efficiency, as demonstrated in Paper E and in the second case study of Paper C.

Second, the potential to improve the real capacity is captured by measuring performance and utilization losses. This can be done in several ways, for example, using work study techniques or automatic data-acquisition systems. However, previous research has identified a decline in work studies (Almström and Kinnander 2011; Bailey and Barley 2005), while the practical difficulties of using automatic data-acquisition systems were identified in Papers D and E. The mere existence of predefined loss categories in systems for automatic data acquisition, or of the system itself, does not guarantee that the information acquired is accurate, as also outlined by Saenz de Ugarte et al. (2009). Paper D found that the loss categories for manual operations were interpreted differently by different operators. Paper E found that more than half of the recorded loss time could not be classified and, moreover, that key parameters representing speed and quality efficiency were left at default values, resulting in a misleading view of the OEE measure.

Finally, Paper F illustrates how national statistics intended to reflect the capacity utilization of industry based on plant-level capacity utilization measures in fact do not represent the internal efficiency of plants. This misleading view of industry is conveyed to policy-makers, who in turn formulate monetary policies that affect the investment behavior of firms. The view is also reported in the daily press, reaching investors and informing decision-makers in firms about the current state of their industries. This research has not investigated the extent to which investors and decision-makers actually make use of official statistics. Though lack of capacity was one of the main motives for offshoring (Bengtsson 2008), a desire to increase capacity utilization in the home country’s existing plants is now a main motive for back-shoring (Dachs and Zanker 2014).

5.2 Quality of research

Empirical research into OM requires that reliability and validity can be demonstrated (Flynn et al. 1990).

5.2.1 Reliability

Reliability concerns whether the results of research are repeatable, which also entails demonstrating that the results did not occur by chance (Bryman and Bell 2007). In case research, this corresponds to the extent to which the operations of a particular study can be repeated with the same results (Yin 2009) and is closely associated with how the empirical data are collected and compiled. The repeatability of the case studies performed in this thesis has been ensured through the use of industrial engineering techniques, which, according to Flynn et al. (1990), can typically be employed to systematically structure the collection of empirical data. The replicability of the multiple case studies reported in Study 0 is considered high, because these studies followed the method described by Sundkvist (2011), which is based on the highly standardized PPA method (Almström and Kinnander 2011). The replicability of Studies I and II is strengthened through the case descriptions and methodology of Papers C and D. Nevertheless, full replicability can never be ensured, because the case studies were performed in production systems that are themselves subject to constant change and evolution.

The replicability of the studies involving secondary analysis has been ensured by describing the methodologies used to model and analyze the data found in the appended papers. Datasets not protected by confidentiality agreements are also available on request.

5.2.2 Validity

Two interrelated aspects of validity need to be considered: first, the validity of the data collected in the empirical studies, which is tested by examining the studies' construct validity, internal validity, and external validity (Voss et al. 2002; Bryman and Bell 2007) and, second, the validity of the model on which the proposed framework is based.

Construct validity, which can also be referred to as measurement validity, states whether or not a construct developed for a phenomenon really reflects the phenomenon it is intended to represent (Bryman and Bell 2007; Landry et al. 1983). This was achieved by incorporating multiple sources of evidence, meaning that the constructs originate from previous production and operation management research, the adoption of international information standards, and the findings of the empirical studies. Construct validity was also the primary focus of RQ1.

Internal validity relates to causality and therefore to the relationships between and internal consistency of constructs when they are assembled in a model (Bryman and Bell 2007). It is directly related to the conceptual validation of models when the researcher investigates whether the problem situation is being considered from the appropriate perspective. It also involves evaluating the extent to which the constructs of the model are linked in order to represent the reality and problem situation (Landry et al. 1983). This was ensured in Studies I and II in which the developed model was systematically evaluated in an empirical context. The outputs from implementing the model, in terms of the capacity frontier diagrams, were presented and discussed with the stakeholders at the case companies.

Moreover, logical validation concerns the capacity of the formal model, or scientific model, to accurately describe the reality and problem situation as defined in the conceptual model (Landry et al. 1983). It is similar to internal validity, as described above, but also entails assessing the impact of the modeling language on the modeling process. This was primarily achieved when the conceptual model was implemented in a software prototype later used to some extent to manage the empirical data collected in Study II. Model validation can also include testing operational validity and experimental validity (Landry et al. 1983); however, these are associated with implementation and model-solving processes and were consequently not the focus of this research.

External validity relates to whether the results of the performed research can be generalized outside the specific research context and to the plausibility, usability, and relevance of the research (Bryman and Bell 2007). This criterion is further discussed in relation to the academic contribution and industrial relevance of the present research in the subsequent sections.

5.3 Academic contribution

The research presented here contributes to the existing body of OM knowledge by proposing the concept of capacity frontiers, an explanatory conceptual framework intended to advance our understanding of the operational improvement potential of production systems. The stated objective was met by demonstrating how the framework can be applied to identify and objectively measure the relevant characteristics of real-life operational processes related to improving shop floor operations. In particular, this contributes to what Bertrand and Fransoo (2002) identify as a weak area in empirical model-based research.

Schmenner and Swink (1998) formulated the theory of performance frontiers after identifying the limitations of microeconomic theory in explaining productivity differences among firms. As outlined, this theory is well established in the OM community and has been applied in previous research to make strategic comparisons both between and within firms. It is acknowledged that the suggested methods and techniques for measuring and constructing the actual frontiers are well suited for strategic decisions and the long-term adaptation of production processes. However, as argued in Section 2.5, the theory's identified shortcomings concern its practical implementation and detailed representation of real operational processes. The lack of cases in which anyone has attempted to graphically plot the asset and operating frontiers using empirical data from a manufacturing context further supports this contention.

In an attempt to bridge the gap between theory and practice, the present research has sought to overcome the practical shortcomings of the theory of performance frontiers by addressing it from an operational perspective. This refers to the measurement and construction of frontiers based on real shop-floor data, using established industrial engineering techniques and existing systems for automatic data acquisition. The original initiative to address the theory of performance frontiers from an operational perspective was made theoretically in the doctoral dissertation of Sundkvist (2014), which also incorporated the production system model. The research presented here has empirically validated the model and further developed the initial work into the capacity frontier framework. The use of the term *capacity frontier* is aligned with the logic of Vastag (2000), who views the asset frontier and operating frontier as analogous to the design capacity and effective capacity of a plant. Singh Srai et al. (2013) interpret this capacity analogy in the same way, applying it in an airline context.

The underlying rationale for relying on direct measurements, as opposed to conceptualizing firm-specific capabilities, is based on the fact that capacity in manufacturing can be expressed in directly measurable constructs, in this case, time. Based on the present findings, this is also required to capture the operational improvement potential. In addition, the development of the capacity frontier framework has been aligned with the recommendations of Rosenzweig and Easton (2010) and Sarmiento et al. (2008) to incorporate longitudinal empirical data to be able to monitor the development of capabilities.

As the capacity frontier framework has been elaborated based on the theory of performance frontiers, the conclusions and explanations presented here are to be interpreted as theoretical propositions, not as constituting a new theory. These theoretical propositions constitute the foundation on which to build more knowledge of the effects on plant-level capacity utilization that come from realizing operational improvement potentials.

5.4 Industrial relevance

The present research was initiated to meet the industrial challenges of achieving sustainable resource utilization and high productivity in operational processes. These challenges have been met by linking firm-level performance measures to the causes of shop-floor productivity losses through the capacity frontier framework. The alignment with established industrial engineering techniques and existing systems for automatic data acquisition promotes the practical applicability of the proposed framework. It can then also be used to evaluate the effects of decisions made. For example, have investments in workforce training increased the real capacity by reducing skill-based performance losses? Has a change in production system layout increased the real capacity or has it resulted in additional disturbances? Have reduced resources assigned to a process, as a result of a policy decision, increased the need-based utilization losses?

In addition, the findings highlight the need to revitalize the industrial engineering competencies needed in order to formulate time standards and to classify and measure time losses for both manual and automatic operations. This is aligned with the conclusions of studies conducted in the Unities States (Bailey and Barley 2005) and Germany (Kuhlang et al. 2014; Kuhlang et al. 2013). As systems for automatic data acquisition are becoming increasingly common due to the ongoing digitalization of industry, it is even more important that companies not distance themselves from managing the fundamental characteristics of their operational processes. In particular, manual operations must be studied in detail. These core competencies are needed to keep operational costs down by efficiently utilizing assets, including both people and equipment. Accurate and updated time standards in planning systems also affect the planning precision in production and, consequently, the ability of firms to perform tasks as expected and to respond to change and unforeseen events. Lastly, a time standard that represents the actual work content of an operation is a prerequisite for ensuring that production is planned so that resources are not forced to exceed their capabilities, risking personal injuries and product quality defects.

6 Conclusions and future research

The purpose of this research was to advance our understanding of the improvement potential of real operational processes. It was formulated to ensure that operational improvement potential is not neglected when strategic decisions are made. This has been accomplished by presenting the analytical logic and structure for deriving the overall productivity and capacity of the operations of a firm from the micro motions and up. This establishes a direct link between firm-level capacity utilization and the causes of shop-floor productivity losses.

The main conclusions are as follows:

- The common measurement unit for all the factors related to capturing the operational improvement potential of capacity or productivity is *time*. This concerns the formulation of planned *time* duration, the measurement of actual *time* duration, and the identification of the factors that cause *time* losses.
- To capture the operational improvement potential, the formulation of a *time* standard is as important as the classification and measurement of *time* losses.
- The quality of *time* data, which directly influence the quality of decisions made at all levels in an organization, depends just as much on the management and on the control and follow-up policies at the tactical and strategic levels as on the actual reporting and acquisition procedures at the operational level.
- It is possible to apply the proposed framework to identify and objectively measure the relevant characteristics of real-life operational processes.

6.1 Future research

It is proposed that the concept of capacity frontiers should be used in future research for the purpose of further developing the predictive power of the framework. This could be done by applying the framework in a setting where the effects on capacity and capacity utilization of different types of operational improvements are further evaluated. Simultaneously, by applying the cash conversion framework of Sundkvist (2014), it would be possible to explore the link between these operational improvements and the corresponding financial effects. An alternative approach would to apply the logic of Singh Srai et al. (2013), i.e., to match changes in operation capabilities (i.e., quality, delivery, cost, and flexibility) with firms' capacity frontiers and financial performance.

Finally, it cannot be guaranteed that operational improvement potential will be realized, even if decision-makers are made aware of it. Strategic decisions related to investments and manufacturing facility locations are made based on many factors. It would accordingly be interesting to further investigate the extent to which knowledge of the operational improvement potential affects decision-maker actions.

References

Adler, Paul S, and Kim B Clark. 1991. "Behind the learning curve: A sketch of the learning process." *Management Science* 37 (3):267-81.

Almström, Peter, and Anders Kinnander. 2008. "Results and conclusions from the productivity potential assessment studies." *Proceedings of the 2nd Swedish Production Symposium*.

Almström, Peter, and Anders Kinnander. 2011. "The productivity potential assessment method: Assessing and benchmarking the improvement potential in manufacturing systems at shop-floor level." *International Journal of Productivity and Performance Management* 60 (7):758-70. doi: 10.1108/17410401111167825.

Almström, Peter, and Mats Winroth. 2010. Why is there a mismatch between operation times in the planning systems and the times in reality? Paper presented at the Proceedings of APMS2010, Cernobbio, Lake Como, Italy.

Amoako-Gyampah, Kwasi, and Jack R Meredith. 2007. "Examining cumulative capabilities in a developing economy." *International Journal of Operations & Production Management* 27 (9):928-50.

Anderson, Philip. 1999. "Perspective: Complexity theory and organization science." *Organization science* 10 (3):216-32.

Andersson, C., and M. Bellgran. 2015. "On the complexity of using performance measures: Enhancing sustained production improvement capability by combining OEE and productivity." *Journal of Manufacturing Systems* 35:144-54. doi: http://dx.doi.org/10.1016/j.jmsy.2014.12.003.

Bacharach, Samuel B. 1989. "Organizational theories: Some criteria for evaluation." *Academy of management review* 14 (4):496-515.

Bailey, Diane E., and Stephen R. Barley. 2005. "Return to work: Toward post-industrial engineering." *IIE Transactions* 37 (8):737-52. doi: 10.1080/07408170590918308.

Balk, Bert M. 2001. "Scale efficiency and productivity change." *Journal of Productivity Analysis* 15 (3):159-83.

Bellgran, Monica, and Eva Kristina Säfsten. 2009. *Production development: design and operation of production systems*: Springer Science & Business Media.

Bengtsson, Alexander, Axel Eriksson, Johan Nänzén, Emelie Roslund, and Carl Swanström. 2014. "Visualisering av produktionsförbättringar." Chalmers University of Technology.

Bengtsson, Lars. 2008. "Outsourcing manufacturing and its effect on engineering firm performance." *International Journal of Technology Management* 44 (3-4):373-90.

Bergström, F, and N Plamkvist. 2014. "An analysis to increase the productivity of a surface mounting line." Master thesis report in Production Engineering.

Bernolak, Imre. 1997. "Effective measurement and successful elements of company productivity: The basis of competitiveness and world prosperity." *International Journal of Production Economics* 52 (1–2):203-13. doi: http://dx.doi.org/10.1016/S0925-5273(97)00026-1.

Bertrand, J Will M., and Jan C Fransoo. 2002. "Operations management research methodologies using quantitative modeling." *International Journal of Operations & Production Management* 22 (2):241-64.

Bhamu, Jaiprakash, and Kuldip Singh Sangwan. 2014. "Lean manufacturing: literature review and research issues." *International Journal of Operations & Production Management* 34 (7):876-940. doi: doi:10.1108/IJOPM-08-2012-0315.

Blair, Johnny, Ronald F Czaja, and Edward A Blair. 2013. *Designing Surveys: A Guide to Decisions and Procedures: A Guide to Decisions and Procedures*: Sage Publications.

Blanchard, Benjamin S, Wolter J Fabrycky, and Walter J Fabrycky. 1990. *Systems engineering and analysis*. Vol. 4: Prentice Hall Englewood Cliffs, New Jersey.

Boer, Harry, Matthias Holweg, Martin Kilduff, Mark Pagell, Roger Schmenner, and Chris Voss. 2015. "Making a meaningful contribution to theory." *International Journal of Operations & Production Management* 35 (9):1231-52. doi: doi:10.1108/IJOPM-03-2015-0119.

Boyer, Kenneth K, and Mark Pagell. 2000. "Measurement issues in empirical research: improving measures of operations strategy and advanced manufacturing technology." *Journal of Operations Management* 18 (3):361-74.

Bryman, Alan, and Emma Bell. 2007. *Business research methods*: Oxford university press.

Cai, Shaohan, and Zhilin Yang. 2014. "On the relationship between business environment and competitive priorities: The role of performance frontiers." *International Journal of Production Economics* 151:131-45.

Chalmers, Alan Francis. 1999. *What is this thing called science?* : Univ. of Queensland Press.

Chen, Chien-Ming, Magali A Delmas, and Marvin B Lieberman. 2015. "Production frontier methodologies and efficiency as a performance measure in strategic management research." *Strategic management journal* 36 (1):19-36.

Chen, David, and Francois Vernadat. 2004. "Standards on enterprise integration and engineering - state of the art." *International Journal of Computer Integrated Manufacturing* 17 (3):235-53.

Choong, Kwee Keong. 2014. "Has this large number of performance measurement publications contributed to its better understanding? A systematic review for research and applications." *Internatioal Journal of Production Research* 52 (14):4174-97.

Clark, Kim B. 1996. "Competing through manufacturing and the new manufacturing paradigm: is manufacturing strategy passé?" *Production and operations management* 5 (1):42-58.

Coelli, Tim, Emili Grifell-Tatje, and Sergio Perelman. 2002. "Capacity utilisation and profitability: A decomposition of short-run profit efficiency." *International Journal of Production Economics* 79 (3):261-78.

Coelli, Timothy J, Dodla Sai Prasada Rao, Christopher J O'Donnell, and George Edward Battese. 2005. *An introduction to efficiency and productivity analysis*: Springer Science & Business Media.

Corrado, Carol, and Joe Mattey. 1997. "Capacity Utilization." *The Journal of Economic Perspectives* 11 (1):151-67. doi: 10.2307/2138256.

Curry, Guy Lee, and Richard Martin Feldman. 2011. *Manufacturing systems modeling and analysis*: Springer.

Czumanski, Thomas, and Hermann Lödding. 2016. "State-based analysis of labour productivity." *Internatioal Journal of Production Research*:1-17.

Da Xu, Li, Wu He, and Shancang Li. 2014. "Internet of things in industries: a survey." *Industrial Informatics, IEEE Transactions on* 10 (4):2233-43.

Dachs, Bernhard, Marcin Borowiecki, Steffen Kinkel, and Thomas Christian Schmall. 2012. "The offshoring of production activities in European manufacturing." *MPRA Paper* (42973).

Dachs, Bernhard, Bernd Ebersberger, Steffen Kinkel, and Bruno R Waser. 2006. "Offshoring of production–a European perspective." *Bulletin Number*.

Dachs, Bernhard, and Christoph Zanker. 2014. "Backshoring of Production Activities in European Manufacturing." *Bulletin Number*.

de Mast, Jeroen, and Joran Lokkerbol. 2012. "An analysis of the Six Sigma DMAIC method from the perspective of problem solving." *International Journal of Production Economics* 139 (2):604-14. doi: http://dx.doi.org/10.1016/j.ijpe.2012.05.035.

Dekkers, Rob. 2015. *Applied systems theory*: Springer.

Dionne, Laura, and Karl G Kempf. 2011. "Data in production and supply chain planning." In *Planning Production and Inventories in the Extended Enterprise*, 167-84. Springer.

Eisenhardt, Kathleen M, and Melissa E Graebner. 2007. "Theory building from cases: opportunities and challenges." *Academy of management journal* 50 (1):25-32.

Elmaghraby, Salah E. 2011. "Production capacity: Its bases, functions and measurement." In *Planning Production and Inventories in the Extended Enterprise*, 119-66. Springer.

Feng, Shaw C., and Eugene Y. Song. 2003. "A manufacturing process information model for Design and Process Planning Integration." *Journal of Manufacturing Systems* 22 (1):1-15.

Filippini, Roberto. 1997. "Operations management research: some reflections on evolution, models and empirical studies in OM." *International Journal of Operations & Production Management* 17 (7):655-70.

Fill, Chris, and Elke Visser. 2000. "The outsourcing dilemma: a composite approach to the make or buy decision." *Management Decision* 38 (1):43-50.

Fisher, Marshall. 2007. "Strengthening the empirical base of operations management." *Manufacturing & Service Operations Management* 9 (4):368-82.

Flynn, Barbara B, and E James Flynn. 2004. "An exploratory study of the nature of cumulative capabilities." *Journal of Operations Management* 22 (5):439-57.

Flynn, Barbara B, Sadao Sakakibara, Roger G Schroeder, Kimberly A Bates, and E James Flynn. 1990. "Empirical research methods in operations management." *Journal of Operations Management* 9 (2):250-84.

Foresight. 2013. " The Future of Manufacturing: A new era of opportunity and challenge for the UK Project report " In. The Government Office for Science, London.

Färe, Rolf, and Valentin Zelenyuk. 2003. "On aggregate Farrell efficiencies." *European Journal of Operational Research* 146 (3):615-20.

Giaglis, GeorgeM. 2001. "A Taxonomy of Business Process Modeling and Information Systems Modeling Techniques." *International Journal of Flexible Manufacturing Systems* 13 (2):209-28. doi: 10.1023/a:1011139719773.

Godinho Filho, Moacir, and Reha Uzsoy. 2013. "Assessing the impact of alternative continuous improvement programmes in a flow shop using system dynamics." *Internatioal Journal of Production Research* 52 (10):3014-31. doi: 10.1080/00207543.2013.860249.

Greenwood, Jeremy, Zvi Hercowitz, and Gregory W Huffman. 1988. "Investment, capacity utilization, and the real business cycle." *The American Economic Review*:402-17.

Hedman, Richard. 2013. "Manufacturing Resource Modelling for Productivity Management - Towards a better understanding the productivity improvement potential at shop floors." Chalmers University of Technology.

Hedman , Richard, Robin Sundkvist , and Peter Almström 2014. Identification of relationships between operator utilization and real process capacity. Paper presented at the The sixt Swedish Production Symposium, Gothenburg, Sweden.

Helmrich, Klaus. 2003. "Productivity process: Methods and experiences of measuring and improving." *International MTM Directorate, Stockholm, Sweden*.

Helo, Petri, Mikko Suorsa, Yuqiuge Hao, and Pornthep Anussornnitisarn. 2014. "Toward a cloud-based manufacturing execution system for distributed manufacturing." *Computers in Industry* 65 (4):646-56. doi: http://dx.doi.org/10.1016/j.compind.2014.01.015.

Hermann, Mario, Tobias Pentek, and Boris Otto. 2015. "Design principles for Industrie 4.0 scenarios: a literature review." *Technische Universität Dortmund, Dortmund*.

Hopp, Wallace J, and Mark L Spearman. 2008. *Factory physics*. Vol. 2: McGraw-Hill/Irwin New York.

IMD. 2004. "SAM - Sequential Activity- and Methods Analysis - System description." In.: International MTM Directorate.

ISA95. 2013. "ANSA/ISA95 Enterprise-Control System Integration - Part 3: Activity Models of Manufacturing Operations Management." In. ANSA/ISA95 .00.03-2013 (IEC 62264-3 Modified)

ISO, 15531-31. 2005. "ISO 15531: Industrial automation systems and integration - Industrial manufacturing management data - Part 31: Resource reference model." In. ISO/TC 184/SC 4.

ISO. 1994. "10303-11: Industrial automation systems and integration product data representation and exchange description methods,:"The EXPRESS Language Reference Manual." In.

Johansen, Leif. 1968. *Production functions and the concept of capacity*: University of Oslo, Institute of Economics.

Jonsson, Patrik, and Magnus Lesshammar. 1999. "Evaluation and improvement of manufacturing performance measurement systems - the role of OEE." *International Journal of Operations & Production Management* 19 (1):55-78. doi: 10.1108/01443579910244223.

Jovane, Francesco, Engelbert Westkämper, and David Williams. 2008. *The ManuFuture road: towards competitive and sustainable high-adding-value manufacturing*: Springer Science & Business Media.

Ketokivi, Mikko, and Thomas Choi. 2014. "Renaissance of case research as a scientific method." *Journal of Operations Management* 32 (5):232-40. doi: http://dx.doi.org/10.1016/j.jom.2014.03.004.

Klassen, Robert D., and Larry J. Menor. 2007. "The process management triangle: An empirical investigation of process trade-offs." *Journal of Operations Management* 25 (5):1015-34. doi: http://dx.doi.org/10.1016/j.jom.2006.10.004.

Klein, Lawrence R., Virginia Long, Alan Greenspan, Douglas Greenwald, Nathan Edmonson, and George Perry. 1973. "Capacity Utilization: Concept, Measurement, and Recent Estimates." *Brookings Papers on Economic Activity* 1973 (3):743-63. doi: 10.2307/2534206.

Kuhlang, P., T. Edtmayr, and W. Sihn. 2011. "Methodical approach to increase productivity and reduce lead time in assembly and production-logistic processes." *CIRP Journal of Manufacturing Science and Technology* 4 (1):24-32. doi: http://dx.doi.org/10.1016/j.cirpj.2011.02.001.

Kuhlang, Peter , Olga Erohin, Matthias Krebs, Jochen Deuse, and Wilfried Sihn. 2013. "The Renaissance of Industrial Engineering Presented in the Example of the Competencies for Time Data Determination." In *International Conference on Competitive Manufacturing*. Stellenbosch University, Matieland, South Africa.

Kuhlang, Peter, Olga Erohin, Matthias Krebs, Jochen Deuse, and Wilfried Sihn. 2014. "Morphology of time data management – systematic design of time data management processes as fundamental challenge in industrial engineering." *International Journal of Industrial and Systems Engineering* 16 (4):415-32. doi: 10.1504/IJISE.2014.060652.

Kuhn, Thomas S. 1996. *The structure of scientific revolutions*: University of Chicago press.

Landry, Maurice, Jean-Louis Malouin, and Muhittin Oral. 1983. "Model validation in operations research." *European Journal of Operational Research* 14 (3):207-20.

Lapré, Michael A., and Gary D. Scudder. 2004. "Performance Improvement Paths in the U.S. Airline Industry: Linking Trade-offs to Asset Frontiers." *Production & Operations Management* 13 (2):123-34.

Lau, R.S.M., Xiande Zhao, and Ming Xiao. 2004. "Assessing quality management in China with MBNQA criteria." *International Journal of Quality & Reliability Management* 21 (7):699-713. doi: doi:10.1108/02656710410549064.

Li, Jingshan, and Semyon M Meerkov. 2008. *Production systems engineering*: Springer Science & Business Media.

Little, John DC. 1961. "A proof for the queuing formula: L= λW." *Operations research* 9 (3):383-7.

Lödding, Hermann. 2012. *Handbook of manufacturing control: Fundamentals, description, configuration*: Springer.

MacCarthy, Bart L, Michael Lewis, Chris Voss, and Ram Narasimhan. 2013. "The same old methodologies? Perspectives on OM research in the post-lean age." *International Journal of Operations & Production Management* 33 (7):934-56.

Manyika, James. 2012. *Manufacturing the Future: The Next Era of Global Growth and Innovation*: McKinsey Global Institute.

Mathur, Alok, GS Dangayach, ML Mittal, and Milind K Sharma. 2011. "Performance measurement in automated manufacturing." *Measuring business excellence* 15 (1):77-91.

Mauri, Federico, Marco Garetti, and Alessandro Gandelli. 2010. "A structured approach to process improvement in manufacturing systems." *Production Planning & Control* 21 (7):695-717. doi: 10.1080/09537280903563485.

Maynard, Harold Bright, Gustave James Stegemerten, and John L Schwab. 1948. *Methods-time measurement*: McGraw-Hill New York.

Meredith, Jack. 1993. "Theory building through conceptual methods." *International Journal of Operations & Production Management* 13 (5):3-11.

Meredith, Jack R, Amitabh Raturi, Kwasi Amoako-Gyampah, and Bonnie Kaplan. 1989. "Alternative research paradigms in operations." *Journal of Operations Management* 8 (4):297-326.

Mitroff, Ian I, Frederick Betz, Louis R Pondy, and Francisco Sagasti. 1974. "On managing science in the systems age: two schemas for the study of science as a whole systems phenomenon." *Interfaces* 4 (3):46-58.

Mousa, Fariss-Terry, and David J. Lemak. 2009. "The Gilbreths' quality system stands the test of time." *Journal of Management History* 15 (2):198-215. doi: doi:10.1108/17511340910943822.

Murgau, Adrian. 2009. *Variety Management for the Industrial Administration*: Chalmers University of Technology.

Muthiah, Kanthi M. N., and Samuel H. Huang. 2006. "A review of literature on manufacturing systems productivity measurement and improvement." *International Journal of Industrial and Systems Engineering* 1 (4):461-84.

Nakajima, Seiichi. 1988. *Introduction to TPM: total productive maintenance*: Productivity Press Cambridge, MA.

Naumann, Justus D. 1986. The role of frameworks in MIS research. Paper presented at the Proceeding of the 1986 DSI National Meeting.

Neely, Andy, Mike Gregory, and Ken Platts. 1995. "Performance measurement system design: a literature review and research agenda." *International Journal of Operations & Production Management* 15 (4):80-116.

Nelson, Randy A. 1989. "On the Measurement of Capacity Utilization." *The Journal of Industrial Economics* 37 (3):273-86. doi: 10.2307/2098615.

Niebel, Benjamin W, and Andris Freivalds. 2003. *Methods, standards, and work design*: McGraw-Hill Boston, MA.

Näringsdepartementet. 2016. "Smart industri – en nyindustrialiseringsstrategi för Sverige." In.: Regeringskansliet.

Obstfeld, Maurice, Kenneth S Rogoff, and Simon Wren-lewis. 1996. *Foundations of international macroeconomics*. Vol. 30: MIT press Cambridge, MA.

Ohno, Taiichi. 1988. *Toyota production system: beyond large-scale production*: crc Press.

OMG. 2013. "Unified Modeling Language (UML), V2.4.1." Object Management Group, Inc., Accessed 2013-07-02. http://www.omg.org/.

Perry, George L. 1973. "Capacity in Manufacturing." *Brookings Papers on Economic Activity* 1973 (3):701-42. doi: 10.2307/2534205.
Popper, Karl. 2002. *The logic of scientific discovery*: Routledge.
Procter, Paul. 1995. "Cambridge international dictionary of English."
Prokopenko, Joseph. 1987. *Productivity management: A practical handbook*: International Labour Organization.
Rasmussen, Svend. 2012. *Production economics: the basic theory of production optimisation*: Springer Science & Business Media.
Robinson, A Ian G, and Margaret M Robinson. 2003. "On the tabletop improvement experiments of Japan." *Frank and Lillian Gilbreth: Critical Evaluations in Business and Management* 2 (3):230.
Rodrique, Jean-Paul, Fadi Farra, Ni Jun, João Carlos Ferraz, and Ludovico Alcorta. 2014. "The Future of Manufacturing: Driving Capabilities, Enabling Investments." In. Geneva, Switzerland: World Economic Forum.
Rosenzweig, Eve D, and George S Easton. 2010. "Tradeoffs in manufacturing? A meta-analysis and critique of the literature." *Production and operations management* 19 (2):127-41.
Rübmann, Michael, Markus Lorenz, Philip Gerbert, Manuela Waldner, Jan Justus, Pascal Engel, and Michael Harnisch. 2015. "Industry 4.0 - The future of productivity and growth in manufacturing industries." In.: The Boston Consulting Group.
Saenz de Ugarte, B, A Artiba, and R Pellerin. 2009. "Manufacturing execution system–a literature review." *Production planning and control* 20 (6):525-39.
Saito, S. 2001. "Case study: reducing labor cost using industrial engineering techniques." In *Maynard's industrial engineering handbook*, edited by Kjell B Zandin, 2.151–2.64. New York: McGraw-Hill.
Sarmiento, Roberto, Joseph Sarkis, and Mike Byrne. 2008. "Manufacturing capabilities and performance: a critical analysis and review." *Internatioal Journal of Production Research* 48 (5):1267-86. doi: 10.1080/00207540802425385.
Schmenner, Roger W, Luk Van Wassenhove, Mikko Ketokivi, Jeff Heyl, and Robert F Lusch. 2009. "Too much theory, not enough understanding." *Journal of Operations Management* 27 (5):339-43.
Schmenner, Roger W., and Morgan L. Swink. 1998. "On theory in operations management." *Journal of Operations Management* 17 (1):97-113. doi: http://dx.doi.org/10.1016/S0272-6963(98)00028-X.
Schoenherr, Tobias, Damien Power, Ram Narasimhan, and Danny Samson. 2012. "Competitive capabilities among manufacturing plants in developing, emerging, and industrialized countries: a comparative analysis." *Decision Sciences* 43 (1):37-72.
Schroeder, Roger G, Rachna Shah, and David Xiaosong Peng. 2011. "The cumulative capability 'sand cone'model revisited: a new perspective for manufacturing strategy." *Internatioal Journal of Production Research* 49 (16):4879-901.
Singh, Harinder, Jaideep Motwani, and Ashok Kumar. 2000. "A review and analysis of the state-of-the-art research on productivity measurement." *Industrial Management & Data Systems* 100 (5):234-41. doi: doi:10.1108/02635570010335271.
Singh Srai, Jagjit, Matthias Holweg, Alka Ashwini Nand, Prakash J Singh, and Damien Power. 2013. "Testing an integrated model of operations capabilities: an empirical study of Australian airlines." *International Journal of Operations & Production Management* 33 (7):887-911.
Skyttner, Lars. 2005. *General systems theory: Problems, perspectives, practice*: World scientific.
Slack, Nigel, Stuart Chambers, and Robert Johnston. 2010. *Operations management*: Pearson Education.
Slack, Nigel, and Michael Lewis. 2002. *Operations strategy*: Pearson Education.

Slack, Nigel, Michael Lewis, and Hilary Bates. 2004. "The two worlds of operations management research and practice: can they meet, should they meet?" *International Journal of Operations & Production Management* 24 (4):372-87.

Sprague, Linda G. 2007. "Evolution of the field of operations management." *Journal of Operations Management* 25 (2):219-38. doi: http://dx.doi.org/10.1016/j.jom.2007.01.001.

Subramaniyan, Mukund. 2015. "Production Data Analytics–To identify productivity potentials." Chalmers University of Technology.

Sundkvist, Robin. 2011. "Linking factory floor productivity to financial measures-A methodology based on production improvements in the electronics production industry."

Sundkvist, Robin. 2014. "Financial benefits of shop floor productivity improvements." Chalmers University of Technology.

Sundkvist, Robin, Richard Hedman, Peter Almström, and A Kinnander. 2012. "Improvement potentials in Swedish electronics manufacturing industry–Analysis of five case studies." *Procedia CIRP* 3:126-31.

Sung, K, J Chang, Z Ridall, H Kalkis, C Tucker, Z Roja, and A Freivalds. 2015. Validation of the Kinect System for Industrial Motion Analysis. Paper presented at the Proceedings 19th Triennial Congress of the IEA.

Szirmai, Adam, Wim Naudé, and Ludovico Alcorta. 2013. *Pathways to Industrialization in the twenty-first century: New challenges and emerging paradigms*: OUP Oxford.

Tangen, Stefan. 2003. "An overview of frequently used performance measures." *Work Study* 52 (7):347-54. doi: 10.1108/00438020310502651.

Tangen, Stefan. 2004. "Evaluation and revision of performance measurement systems."

Tangen, Stefan. 2005. "Demystifying productivity and performance." *International Journal of Productivity and Performance Management* 54 (1):34-46. doi: 10.1108/17410400510571437.

Taylor, Andrew, and Margaret Taylor. 2009. "Operations management research: contemporary themes, trends and potential future directions." *International Journal of Operations & Production Management* 29 (12):1316-40.

Taylor, Frederick. W. 1911. "The principles of scientific management." *New York & London: Harper Brothers*.

Tippett, LHC. 1935. "A snap reading method of making time studies of machines and operatives in factory surveys." *Journal of the British Textile Institute Transactions* 26:51-5.

UNIDO. 2013. "The Industrial Competitiveness of Nations–Looking back, forging ahead." In. Vienna: United Nations Industrial Development Organization (UNIDO).

Wacker, John G. 1998. "A definition of theory: research guidelines for different theory-building research methods in operations management." *Journal of Operations Management* 16 (4):361-85.

Walker, Helen, Daniel Chicksand, Zoe Radnor, and Glyn Watson. 2015. "Theoretical perspectives in operations management: an analysis of the literature." *International Journal of Operations & Production Management* 35 (8):1182-206.

Ward, Peter T., John K. McCreery, Larry P. Ritzman, and Deven Sharma. 1998. "Competitive Priorities in Operations Management." *Decision Sciences* 29 (4):1035-46. doi: 10.1111/j.1540-5915.1998.tb00886.x.

Vastag, Gyula. 2000. "The theory of performance frontiers." *Journal of Operations Management* 18 (3):353-60.

Westkämper, Engelbert. 2013. *Towards the Re-industrialization of Europe: A Concept for Manufacturing for 2030*: Springer Science & Business Media.

Vichare, Parag, Aydin Nassehi, Sanjeev Kumar, and Stephen T Newman. 2009. "A Unified Manufacturing Resource Model for representing CNC machining systems." *Robotics and Computer-integrated Manufacturing* 25 (6):999-1007.

Wilson, James M. 2013. "Henry Ford vs. assembly line balancing." *International Journal of Production Research:*1-9. doi: 10.1080/00207543.2013.836616.

Von Bertalanffy, Ludwig. 1950. "An outline of general system theory." *British Journal for the Philosophy of science*.

Von Bertalanffy, Ludwig. 1972. "The meaning of general system theory." *General system theory: Foundations, development, applications*:30-53.

Voss, Chris, Nikos Tsikriktsis, and Mark Frohlich. 2002. "Case research in operations management." *International Journal of Operations & Production Management* 22 (2):195-219.

Wu, Bin. 2012. *Manufacturing systems design and analysis*: Springer Science & Business Media.

Yin, Robert K. 2009. *Case study research: Design and methods*. Vol. 5: Sage.

Yusof, Yusri, and Kamran Latif. 2014. "Survey on computer-aided process planning." *The International Journal of Advanced Manufacturing Technology* 75 (1-4):77-89.

Zandin, Kjell B. 2001a. *Maynard's industrial engineering handbook*: McGraw-Hill New York, NY.

Zandin, Kjell, B. 2001b. "Work sampling and group timing technique." In *Maynard's Industrial Engineering Handbook, Fifth Edition*. McGraw Hill Professional, Access Engineering.

Zhang, Lin, Yongliang Luo, Fei Tao, Bo Hu Li, Lei Ren, Xuesong Zhang, Hua Guo, Ying Cheng, Anrui Hu, and Yongkui Liu. 2014. "Cloud manufacturing: a new manufacturing paradigm." *Enterprise Information Systems* 8 (2):167-87. doi: 10.1080/17517575.2012.683812.