Product Variety Management in Process Industry Companies

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PREFACE

This PhD thesis is based on an Industrial PhD project conducted by Alexandria Lee (Moseley) Trattner in collaboration with the Technical University of Denmark, the Danish Innovation Fund and a global producer of insulation materials. The project was completed over three and a half years from 1 October 2015 to 31 March 2019, with this thesis serving as a culminating work of the project. A leave of absence of six months was taken in the middle of the project period to focus on other work at the insulation company.

The PhD thesis is article-based and incorporates content from eight studies used to answer three research questions (RQs). The principle aims of this work are to provide greater insight into the effect of increasing product variety on operational performance in the process industry and to provide useful tools for managers to mitigate the negative impact of product variety. A summary of the articles in relation to the research questions is presented. In addition to the articles, business perspectives from a longitudinal case study of product variety reduction at a process industry manufacturer are presented and discussed in this report.

RQ 1: How does product variety impact operational performance in industrial companies?


RQ 2: What is the magnitude of the impact of product variety on process productivity?


**RQ 3: What methods can be used to better manage product variety in process industries?**


Full-text versions of the articles are appended to the end of this thesis. It should be noted that Studies C, D and F are based on analyses performed by master’s thesis students at DTU, which have been supervised, replicated and adapted by the author. Furthermore, most of the data collection and analysis for Study H was performed prior to the PhD studies, while some post analysis and the journal article writing and peer-review processes were performed during the PhD studies.

Alexandria Lee Trattner, Kongens Lyngby, 30 March 2019
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I would first like to thank my supervisor Lars Hvam for his continuous guidance and support throughout the PhD programme, Zaza Nadja Lee Herbert-Hansen for her supervision, feedback and co-authorship on many of my papers and the PhD students and Post-Docs in my research group who have helped me navigate the PhD rollercoaster the past three years (Katrin Kristjansdottír, Anna Myrodia, Samuel Larsen, Diana Feibert, Loris Battistello, Franziska Schorr, Michael Bayer, Amartya Ghosh, Daniel Sepúlvada and Matteo Perno, to name a few). I would also like to thank Cipriano Forza at the University of Padova for helping me to frame my research and for hosting me on my external research stay.

To all my colleagues and managers at the company who provided me the opportunity to roll up my sleeves in the fight against complexity and create real change in a large-scale organization, I also extend my heartfelt thanks. Among the people I owe specific thanks are Martin Berg for being the catalyst who started the complexity management project and trusted me to take the reins, Henrik Hedelund Nielsen and Martin Middelboe Frederiksen for being two of the most competent analysts and sparring partners I have ever worked with, Dorthe Lybye for her kind review of my academic publications, Bjørn Rici Andersen for his clear-cut leadership and for his championing of my professional growth, and Jens Birgersson for his consistent support of the project’s implementation over the past three years. I also thank the students who have contributed to my project in pursuit of their MSc. degrees, including Lea Greiling, Fabio Labrini, Christian Haim Raben, Eduardo Pereda Pons, Victor Aguasca Lloberes, Waqas Khalid, and Elizabeth Yanchapaxi.

Massive thanks are due to the Danish Innovation Fund and tax payers of Denmark for making this project a fiscal reality. I hope you continue to support international students like myself, thereby drawing the world’s top talent and accelerating the development of Denmark’s private sector.

Finally, this project would not have been possible without the support of my family, friends, and church community at Hillsong Copenhagen who have been my biggest cheerleaders. I thank my husband, Andreeas, for his constant love and encouragement which motivated me to run my race and finish well. Lastly, I thank my God for His faithfulness to me. In bringing me to Denmark six years ago and blessing me with a life I honestly could never have dreamed up myself, He has proven to me that all things truly are possible.
SUMMARY

Coping with increasing product variety has been a principal industrial challenge for industries in the age of globalisation, mass customisation and more selective customers. A broad product portfolio can require increased product changeovers, reduced production efficiencies, more complex production planning and reduced service level towards end customers. A high product variety in particular is a challenge for process industry companies, which are characterised by large, expensive, automated equipment designed to mass produce a narrow product range.

This thesis presents a set of eight studies that examine the relationship between product variety and operational performance from multiple perspectives. First, the way product variety affects operational performance in industrial companies is described through a systematic literature review. Next, using various quantitative regression techniques, this study builds on the literature by quantifying the magnitude of the impact of product variety on process productivity using multiple cases at a process industry manufacturer. Last, a set of methods is presented to better manage product variety without compromising operational and financial performance. Each method is tested using a case study of different process industry firms.

Based on the academic literature, the results show that increasing product variety in manufacturing and supply chain firms is related to increased cost and reduced time performance and is only slightly related to reduced quality and delivery performance. Through the quantitative studies, it is shown that the specific impact of product variety on production productivity operationalises itself in a process industry setting as smaller batch sizes, increased changeover waste and higher process variability, resulting in reduced operating speed. Methods shown to improve the management of product variety in process industry firms include production planning methods, such as the product wheel, a framework for analysing lost production speed and a product portfolio optimisation tool. These findings, along with findings related to a longitudinal product variety reduction at a case company within the process industry, provide insights for academics and practitioners regarding the nature of the relationship between product variety and operational performance as well as the methods by which the relationship can be managed.
Resumé (Danish)

Håndtering af stigende produktvariation har været en af industriens største industrielle udfordringer i en tid defineret af globalisering, mass customisation og mere selektive kunder. En bred produktportefølje kan kræve flere omstillinger i produktionen, reduktion af produktionseffektivitet, mere kompleks produktionsplanlægning, samt reduktion i serviceniveauet for slutkunden. Høj produktvariation er især en udfordring for industrivirksomheder, karakteriseret ved stort, dyrt og automatiseret udstyr, designet til masseproduktion af et smalt produktsortiment.

Denne afhandling præsenterer otte studier, der undersøger forholdet mellem produktvariation og operationel ydeevne set fra flere vinkler. For det første afdækker vi, hvordan produktvariation påvirker driftspræstationen i industrivirksomheder gennem et systematisk litteraturstudie. Ved hjælp af forskellige kvantitative regressionsteknikker udbygger vi litteraturen ved at kvantificere indflydelsen af produktvariation på procesproduktivitet, baseret på resultaterne af flere casestudier fra en virksomhed med kontinuerligt flow produktion. Til sidst, udarbejder vi et sæt metoder til bedre at styre produktvariation, uden at gå på kompromis med operationelle og økonomiske resultater. Hver metode testes ved hjælp af et casestudie i forskellige virksomheder med kontinuerligt flow produktion.

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<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>ABC</td>
<td>Activity-based costing</td>
</tr>
<tr>
<td>BU</td>
<td>Business unit</td>
</tr>
<tr>
<td>CC</td>
<td>Complexity cost</td>
</tr>
<tr>
<td>CM</td>
<td>Contribution margin (net sales – cost of goods sold)</td>
</tr>
<tr>
<td>ELS</td>
<td>Economic lot size</td>
</tr>
<tr>
<td>ERP</td>
<td>Enterprise resource planning system</td>
</tr>
<tr>
<td>GAMS</td>
<td>General Algebraic Modelling System</td>
</tr>
<tr>
<td>KPI</td>
<td>Key performance indicator</td>
</tr>
<tr>
<td>MES</td>
<td>Manufacturing execution system</td>
</tr>
<tr>
<td>MIP</td>
<td>Mixed integer program</td>
</tr>
<tr>
<td>MOSFT</td>
<td>Maximum observed, sustainable, feasible throughput</td>
</tr>
<tr>
<td>MTO</td>
<td>Make-to-order</td>
</tr>
<tr>
<td>MTS</td>
<td>Make-to-stock</td>
</tr>
<tr>
<td>OEE</td>
<td>Overall equipment effectiveness</td>
</tr>
<tr>
<td>OM</td>
<td>Operations management</td>
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<tr>
<td>OP</td>
<td>Operational performance</td>
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<tr>
<td>OR</td>
<td>Operations research</td>
</tr>
<tr>
<td>PC</td>
<td>Product complexity</td>
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<tr>
<td>PF</td>
<td>Product family</td>
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<tr>
<td>PIM</td>
<td>Product information management</td>
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<tr>
<td>PV</td>
<td>Product variety</td>
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<tr>
<td>SKU</td>
<td>Stock keeping unit</td>
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<tr>
<td>TPM</td>
<td>Total productive maintenance</td>
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1 INTRODUCTION

“There is no perfect Pepsi, only perfect Pepsis.” - Howard Moskowitz

The days of finding the one perfect product to satisfy the needs of all customers have ended. In his work with PepsiCo, the renowned market researcher Howard Moskowitz expressed this point in the quote above advising PepsiCo to find the best set of Pepsis to offer to the market and give up efforts to find the magic recipe which would maximise customer satisfaction (Gladwell, 2004). Henry Ford’s Model T automobile, which famously came ‘in any colour as long as it’s black’, epitomised the era of mass production where manufacturing systems could be finetuned to produce a single product variant as efficiently as possible; however, manufacturers currently operate in a new era in which the right level of product variety must be offered to satisfy market demands while maintaining operational efficiencies.

1.1 THE RISE OF PRODUCT VARIETY AND PRODUCT VARIETY MANAGEMENT

Manufacturing companies are expanding the variety of their product offerings due to factors such as increased competition due to globalisation (Lee, 1996; Ulrich, 2006), more selective, heterogeneous customers desiring new products (Quelch and Kenny, 1995; Ulrich, 2006) and technological change (Lee, 1996). Industrial trends driving manufacturers to increase their product lines include mass customisation, or the art of tailoring products and services to the individual needs of customers (Pine, 1993), and the use of customer segmentation to drive product development (Quelch and Kenny, 1995). Companies possessing underutilised fixed assets are also known to extend product lines to potentially increase sales and thereby to better utilise their equipment (Götzfried, 2013; Quelch and Kenny, 1995). One set of authors summarised these trends, stating that ‘companies can no longer follow the trail blazed by Henry Ford, capturing market share and high profits by producing large volumes of a standardized product. Today, customers’ needs and wants change rapidly’ (MacDuffie et al., 1996, p. 350).

The expansion of product lines at industrial companies is a cross-industry phenomenon. Examples of expanded product offerings are numerous with documented increases, such as in the number of spaghetti sauces (Quelch and Kenny, 1995), toothpastes (Quelch and Kenny, 1995), food and beverage products (Baumann and Trautmann, 2014; Bilgen and Günther, 2010), cleaning products (Van Hoek and Pegels, 2006), chemical products (Ashayeri and Selen, 2001; Berry and Cooper, 1999), steel products (Balakrishnan and Geunes, 2003; Storck, 2010), car models (Holweg and Pil, 2005), sporting goods (Appelqvist et al., 2013) and clothing products (Berman, 2011).

Manufacturers can broaden their portfolios by introducing new products, adding new functionality to existing products, offering new packaging types or customising products to meet the
individual needs of the customer (Brun and Pero, 2012). Market expansion and the associated increase in product documentation and package labelling can also influence the number of product variants (Bilgen and Günther, 2010); however, companies are not always aware of the benefits as well as the drawbacks of increasing product variety.

Product variety is regarded as beneficial for a company if the product variety leads to marketplace advantages, such as increased revenue and market share, at a low cost (MacDuffie et al., 1996; Wilson and Perumal, 2009). Evidence supports that product line expansions can help firms increase their market share in competitive industries, such as fast-moving consumer goods (Quelch and Kenny, 1995); however, there are additional operational costs imposed on production and supply chain systems when product variety is increased. Increasing product variety can lead to increased production complexity, greater difficulty in forecasting, diluted brand value and increased supplier costs (Quelch and Kenny, 1995). One study of 255 senior executives showed that high levels of product variety were not correlated with increased profitability but rather were correlated with increased customer and employee difficulties (Mocker and Ross, 2017). Another study showed that a large number of components led to missing parts and late deliveries for the electronics producer HP (Ward et al., 2010). The simultaneous advantages and disadvantages of adding product variety has left members of industry and academia unsure of what constitutes good product variety and good product variety management.

Along with the rising levels of product variety and the corresponding complexity in business processes is the increase of published product variety and complexity management techniques. Practitioner books, such as Waging War on Complexity Costs (Wilson and Perumal, 2009) and The Complexity Crisis (Mariotti, 2008), catapulted product and process complexity to the centre of business discussions in the 2000s. Management consultancies also entered the complexity management arena, publishing white papers and articles in trade journals that offer their own brands of short-term and long-term strategies for simplifying product assortments and business processes (AT Kearney, 2009; Gottfredson and Schwedel, 2008; KPMG, 2011; PA Consulting, 2015; Peter et al., 1991; Sargut and McGrath, 2011). The management of product variety and product complexity is also a popular topic in academic literature and a common subject of doctoral dissertations (Götzfried, 2013; Marti, 2007; Myrodia, 2016; Webb, 2011) and journal articles (Van Iwaarden and Van der Wiele, 2012; Perona and Miragliotta, 2004; Scavarda et al., 2010; Smith and Escobar-Saldivar, 2006; Ward et al., 2010). Understanding the specific ways that product variety impacts critical business processes, quantifying the effect of product variety on financial and operational performance and using various techniques to optimise the level of product variety and to enable more efficient manufacturing are crucial to these methods.

While the increase in product variety is experienced across industries, much of the literature on product variety management has focused on the automotive and electronics sectors (Brabazon et al., 2010; Ding et al., 2007; Fisher and Ittner, 1999; Holweg and Pil, 2005; MacDuffie et al., 1996; Moreno and Terwiesch, 2017; Novak and Eppinger, 2001; Ward et al., 2010), with fewer studies investigating the needs of the producers of food, beverages and other
high-volume, raw materials characteristic of the process industry (Anderson and Sedatole, 2013; Berry and Cooper, 1999; Cooke and Rohleder, 2006; Denton et al., 2003; Wan et al., 2012). Some authors have specifically cited the dearth of academic inquiry on product variety and complexity in the process industry, noting the challenge in studying these products because much of the processing occurs at the molecular level (Orfi et al., 2011). Considering the large role that the process industry plays in the economy, contributing to 41% of revenue from all manufacturing firms in Europe in 2016\(^1\), the lack of academic inquiry on the process industry should not be ignored.

From an industry perspective, complexity caused by increased product variety and other factors is a primary issue faced by companies in the process industry. A survey of managers at chemical companies and process companies revealed that 72% of managers considered complexity management to be one of their top priorities in running their businesses (PwC, 2013). A further challenge of increased product variety for process industry manufacturers is that their production systems are intrinsically more rigid than the systems of other industries because they are designed to produce narrow ranges of products in high volumes (Balakrishnan and Geunes, 2003; Yeh and Chu, 1991). In the process industry, increased product variety can lead to reduced batch sizes, increased setup and changeover time, increased waste and lower productivity (Berry and Cooper, 1999). The costs of these inefficiencies are particularly high in the process industry due to the high cost of capital equipment, which cannot be changed frequently, and the long changeovers required between production runs (Fransoo, 1992).

The alignment of the product strategy and the production process strategy has been discussed as a key component of effective business strategies (Hayes and Wheelwright, 1979; Safizadeh et al., 1996; Skinner, 1974). The product-process matrix developed by Hayes and Wheelwright (1979) (see Figure 1-1) shows that manufacturers typically adopt product and process structures along the diagonal of the matrix, with companies in the process industry typically located in the bottom right corner. An empirical analysis of the product-process matrix has shown that around 75% of companies’ process structures are found in the diagonal of the product-process matrix (Safizadeh et al., 1996); however, as the demand for greater product variety pervades more industrial companies and as process technology becomes more flexible and automated, process industry firms may produce increasingly smaller batch sizes, moving them from the diagonal of the product-process matrix to potentially new operational paradigms.

\(^1\) Figures from EuroStat Annual detailed enterprise statistics for industry (NACE Rev. 2. B-E), Year: 2016, Geopolitical entity: European Union (28 countries), Codes: C10 food products, C11 beverage products, C17 pulp and paper products, C19 coke and refined petroleum products, C20 chemicals and chemical products, C21 basic pharmaceutical products and pharmaceutical preparations, C23 non-metallic mineral products, and C24 basic metals.
Despite the substantial literature in the field of product variety management, there is still a need to better understand how product variety impacts the manufacturing system (Stäbli et al., 2011), particularly for process industry manufacturers being pressured to produce smaller batch sizes. This thesis presents a multi-dimensional view of this topic, aiming to identify the ways in which product variety impacts operational performance in the process industry, to quantify the identified impact and to propose methods by which product variety and its effects can be managed. The following sections introduce the research questions that guided the inquiry of this thesis and the chosen domain of the process industry.

1.2 Research aim and research questions
The overall objective of this research was to investigate product variety proliferation and management techniques within the process industry. Three research questions (RQs) were formulated to guide the research process. The RQs reflect the overlap of the practical needs of an industrial collaboration partner operating in the process industry and relevant gaps in the academic literature.
Understanding the current research on the impact of product variety on operational performance in different settings is fundamental to product variety management. Thus, RQ1 was formulated as a relationship-defining ‘how’ question to obtain this understanding (Larsen, 2017; Yin, 2018). RQ1 was used to guide the review of the literature and empirical research to identify trends regarding whether increasing product variety is beneficial or detrimental to firm performance. As the literature on the process industry is not highly prevalent in operations management literature, the focus of this question was scoped more broadly to encompass all industrial companies.

**RQ 1: How does product variety impact operational performance in industrial companies?**

The second research question narrows the scope of analysis to quantify the impact of product variety on process productivity, a key measure of operational performance in process industry settings (Berry and Cooper, 1999). The predominant relationships identified based on RQ1 will direct the quantitative study of RQ2 where a specific relationship is analysed to reveal its magnitude and thus its relative importance to the organisation. RQ2 primarily addresses measuring the potential for process productivity improvement by optimising product variety and other relevant variables.

**RQ 2: What is the magnitude of the impact of product variety on process productivity in the process industry?**

The third research question broadened the research focus slightly by exploring methods by which product variety and its effects on performance can be managed in process industries. The findings based on RQ2 helped pinpoint how product variety operationalises itself in relation to performance measures, such as process productivity. Using this knowledge, methods can be identified or developed based on the literature and can be tested in process industry case companies to determine their effectiveness in supporting product variety management.

**RQ 3: What methods can be used to better manage product variety and its effects on the process industry?**

### 1.3 Domain Limitation: The Process Industry

The American Production and Inventory Control Society (APICS) defines process industries as ‘manufacturers that produce products by mixing, separating, forming and/or performing chemical reactions [such as] paint manufacturers, refineries and breweries’ (Pittman and Atwater, 2016). These companies produce relatively basic materials, such as glass, ceramics, stone, clay, steel, metal, chemicals, food, beverages, textiles, lumber, wood and pulp and paper. While the complexity level of these end products may appear to be low, there is complexity at
the molecular level in the materials and in the processes used to create them (Orfi et al., 2011). The term 'process industry' in this paper is used in alignment with the APICS definition.

The characteristics of manufacturers in the process industry that distinguish them from discrete manufacturers include: capital intensive production technology (Van Kampen and Van Donk, 2013), batch or continuous flow processes (Crama et al., 2001), high volume production (Abdulmalek et al., 2006), high environmental demands and regulations (Crama et al., 2001), use of recipes rather than bills of material (Crama et al., 2001), low work in process inventory (Ljungberg, 1998; Nakajima, 1989), focus on campaigns running similar products between major cleanings (Amaran and Bury, 2016; Crama et al., 2001; ElMaraghy et al., 2013), long sequence-dependent setup times (Berry and Cooper, 1999; Cooke and Rohleder, 2006) and the presence of a discretisation point (i.e. a phase in production when the product shifts from a continuous form to a discrete form in individual packaging) (Abdulmalek et al., 2006). Due to the commodity nature of many of the products, process industries are more likely to compete based on price and delivery speed rather than product differentiation when compared to discrete industries (Crama et al., 2001; Porter, 1985).

The transformation of inputs to outputs also differs between discrete and process industries. A depiction of the patterns along which variety is transformed from input to output in different production systems is shown in Figure 1-2. Discrete industries typically utilise bills of material to structure the assembly of many components and raw materials into a low number of end products, such as in printer or aircraft production (Crama et al., 2001). Process industries are known to use recipes for the transformation of a limited number of raw materials into a greater number of end items, such as for a blending process or beverage bottling process (Crama et al., 2001).

Researchers have discussed that process industries lag in adopting the latest management developments due to the capital intensive nature of the process and the low influence of manual labour (Cooke and Rohleder, 2006; Dennis and Meredith, 2000). Even aspects of Lean manufacturing have required adaptation from the widely known automotive production context to
the process industry context (Abdulmalek et al., 2006; King, 2009). Researchers have argued that process manufacturers with early process discretisation points have more opportunities for the application of Lean manufacturing principles due to the increased similarity to discrete industries (Abdulmalek et al., 2006).

1.4 STRUCTURE OF THIS THESIS

In the sections which follow, the theoretical background of the constructs employed in this thesis is presented (Section 2), followed by a description of the thesis’ mixed-methods research design (Section 3). In Section 4, the operational impact of PV is examined using two systematic literature reviews to answer RQ1. Section 5 presents the results of three regression analysis studies that were used to quantify the magnitude of the impact of product variety on process productivity using multiple cases at a process industry manufacturer, thus answering RQ2. In Section 6, a set of methods to better manage product variety without compromising operational and financial performance is presented in response to RQ3. Section 7 presents a longitudinal case study of product variety management at an international manufacturing company operating within the process industry. Lastly, Sections 8 and 9 present the discussion and conclusions, respectively.
2 THEORETICAL BACKGROUND

‘Any intelligent fool can make things bigger, more complex, and more violent. It takes a touch of genius—and a lot of courage to move in the opposite direction’. - E. F. Schumacher

Product variety management is a multi-faceted field built on the contributions from the marketing, economics and operations management (OM) domains (Lancaster, 1990; Ramdas, 2003). In their seminal work on product variety management, ElMaraghy et al. (2013) discuss the competing interests of marketers, who would like to expand product lines to appease customers, and supply chain managers, who prefer a limited product variety to increase internal efficiencies. These dichotomous views on product variety management are fundamental to understanding and to framing the contributions of this thesis.

In the following sections, the theoretical background of this thesis is presented. The topics discussed include the main constructs used in this study, the market-facing and operational perspectives of product variety management, a summary of available product variety management frameworks and gaps in existing research.

2.1 DEFINITION OF CONSTRUCTS

The academic inquiry of this thesis involves four primary constructs: product variety (PV), product complexity (PC), product variety management and operational performance (OP).

A myriad of measures related to PV and PC have been proposed by researchers, each describing either the location where variety manifests, the specific ways in which products vary or the design and production complexity of individual products. An illustration of the PV and PC terms is provided in Figure 2-1, and a table of relevant PV and PC measures from the literature is presented in Table 2-1.

‘PV’ is a term with an agreed upon definition amongst researchers as the number of finished goods produced by a firm (Berry and Cooper, 1999; Mapes et al., 1997; Pil and Holweg, 2004; Pine, 1993; Wan et al., 2012). The term ‘variety’ can also be used to describe component and process variety (Orfè et al., 2011). As shown in Figure 2-1, PC encompasses more than the sheer number of products, components or options offered to the customer. PC can also refer to the multiplicity, diversity and interrelatedness of components within a product (Götzfried, 2013; Jacobs, 2013) or to the degree of a product’s novelty (Ding et al., 2007; Novak and Eppinger, 2001). Unfortunately, the definitions of PV and PC are often misconstrued in OM literature (Moseley, Hvam, et al., 2017), thus warranting a formal definition in this study. Throughout this study, PV refers to the number of finished goods produced by a company or a
production line, and PC refers to the broader concept of multiplicity, diversity and interrelatedness of components, options and product variants offered by a firm. In this way, PC serves as an umbrella term containing PV and other product-related measures.

**Figure 2-1 Illustration of variety and product complexity**

PV management, the third construct used in this study, is the process of making decisions related to the product offering of a firm (Götzfried, 2013; Ramdas, 2003). These decisions are made at different times and in different functions of the business and can focus on PV creation (e.g. new product launch) or PV implementation (e.g. how to source components and to produce the product) (Ramdas, 2003).

OP is a fourth construct that is fundamental to this study. Determining how to evaluate the performance of operational functions, such as manufacturing and logistics, has been a topic of research within OM for some time (Ferdows and De Meyer, 1990; Fine and Hax, 1985; Swink and Hegarty, 1998). Measures of OP typically include operational costs for production, inventory and logistics, product quality, inventory turns, lead time, productivity and delivery reliability (Ferdows and De Meyer, 1990; Filippini et al., 1998; Fine and Hax, 1985; Squire et al., 2006). While flexibility is regarded as an OP measure by some authors (Ferdows and De Meyer, 1990), others argue that flexibility is a capability rather than an operational outcome (Swink and Hegarty, 1998). Based on the literature, the term ‘OP’ in this study refers to a firm’s cost, time, quality and delivery performance. The measures are explored broadly in relation to manufacturing systems, basic production-distribution systems and supply chains with specific performance measures analysed in each study.
Table 2-1 Measures related to product variety used in the literature

<table>
<thead>
<tr>
<th>Measure</th>
<th>Definition</th>
<th>Source(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product variety</td>
<td>The number of different products offered to customers</td>
<td>(Pine, 1993)</td>
</tr>
<tr>
<td></td>
<td>The number of end products or stock keeping units (SKUs) offered by a firm which differ in fit (e.g. size), taste (e.g. colour) and quality from the customer’s perspective</td>
<td>(Ulrich, 2006)</td>
</tr>
<tr>
<td>Product complexity</td>
<td>A measure of a product’s sophistication based on the number of components within the product, the level of interaction between the components and the degree of product novelty</td>
<td>(Ding et al., 2007; Novak and Eppinger, 2001)</td>
</tr>
<tr>
<td>Product proliferation</td>
<td>The expansion of existing product lines with new variants</td>
<td>(Berman, 2011)</td>
</tr>
<tr>
<td>Product variegation</td>
<td>The ways in which products differ from one another</td>
<td>(Ramdas, 2003)</td>
</tr>
<tr>
<td>Product line breadth</td>
<td>The number of different models produced by a firm</td>
<td>(Moreno and Terwiesch, 2017)</td>
</tr>
<tr>
<td>Product mix</td>
<td>A measure of the demand distribution across products in a company’s portfolio</td>
<td>(Akkerman and van Donk, 2009)</td>
</tr>
<tr>
<td>Product portfolio architectural complexity (PPAC)</td>
<td>A combination of three measures detailing the multiplicity, diversity and interrelatedness of products within a product portfolio</td>
<td>(Jacobs and Swink, 2011)</td>
</tr>
<tr>
<td>External variety</td>
<td>The theoretical number of product variants offered to customers</td>
<td>(Fisher and Ittner, 1999; Pil and Holweg, 2004)</td>
</tr>
<tr>
<td>Internal variety</td>
<td>The variety ordered by customers and handled by the value chain</td>
<td>(Pil and Holweg, 2004)</td>
</tr>
<tr>
<td></td>
<td>Variety in product attributes measured as fundamental variety (variety in models), intermediate variety (variety in parts) and peripheral variety (variety in options)</td>
<td>(MacDuffie et al., 1996)</td>
</tr>
<tr>
<td>Horizontal product differentiation</td>
<td>Products of similar quality with different characteristics in the same offering</td>
<td>(Lancaster, 1990)</td>
</tr>
<tr>
<td>Vertical product differentiation</td>
<td>Products with different levels of product quality in the same offering</td>
<td>(Lancaster, 1990)</td>
</tr>
</tbody>
</table>

2.2 Market perspectives on product variety

Variety is often added to increase the market share of a company or to differentiate a firm’s products in the marketplace (Kekre and Srinivasan, 1990; Porter, 1985; Xia and Rajagopalan, 2009). PV may also be introduced for strategic purposes, such as pre-emptively differentiating the product portfolio to beat competitors to market, though the initial profitability of the expanded portfolio may not be very high (Lancaster, 1990). Increased PV leads to an increased utility of the product assortment from the customer perspective, as the customers are more likely to order exactly what they need (ElMaraghy et al., 2013). Methods have been developed to optimise the selection of products to maximize market share (Green and Krieger, 1989). Broader product lines can also lead to higher revenues and profits (Xia and Rajagopalan, 2009) because customers will pay a premium for higher quality products if the products are vertically differentiated (i.e. variegated in terms of quality levels) (Ulrich, 2006).
Using four years of retail sales data, Ton and Raman (2010) show that increasing PV has a positive direct effect on total store sales. In another study, sales were found to grow in a diminishing fashion with respect to increasing variety (Wan et al., 2012), a pattern which has been attributed to the cannibalisation of demand (Ramdas and Sawhney, 2001).

In a study of a beverage producer, Wan et al. (2012) show that there are both direct and indirect effects of PV on sales. They posit that ignoring the indirect effects of PV may lead to an overestimation of the benefits of PV and that an excessive increase in PV may not be beneficial for the firm.

Despite the espoused market benefits, research has shown that not all variety additions lead to increases in profits (Ramdas and Sawhney, 2001). Increasing variety can be accompanied by increasing costs (Xia and Rajagopalan, 2009) and customer confusion due to difficulty in distinguishing products from one another (Huffman and Kahn, 1998). Variety induced complexity is also discussed in the literature as the additional cost imposed on the business, production and supply chain processes of a firm by proliferating product variants and product features (ElMaraghy et al., 2013). Effective PV management can balance the benefits and costs of variety in decision making (Lancaster, 1990).

2.3 Operational Perspectives of Product Variety

PV has long been touted as an enemy to increased OP along the value chain as economies of scale are eroded in exchange for economies of scope (Lancaster, 1990; Ulrich, 2006). The relationship between PV and OP is investigated using a systematic literature review in Section 4, but a brief introduction to the topic is provided in this section.

As the number of products increase, it has been shown that the expected inventories and backorders increase linearly in a simple integrated production-distribution system (De Groote and Yücesan, 2011). Other authors have shown that the inventory cost of holding PV is proportional to the square root of the number of products stocked (Eppen, 1979; Zipkin, 1995). Other studies have linked increased variety with longer lead times (Thonemann and Bradley, 2002), more complex sourcing and increased outsourcing (ElMaraghy et al., 2013), an increased learning curve in operations (ElMaraghy et al., 2013) and higher defect rates (Ton and Raman, 2010).

Regarding labour productivity, a set of studies performed to examine the automotive industry revealed that only certain types of PV induce lower productivity among operators, while some PV has no effect on performance (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996). PV has also been shown to contribute to lost process productivity (i.e. reduced throughput, increased setup times or reduced quality) on continuous and batch production lines in the chemical, textile and glass industries (Anderson and Sedatole, 2013; Anderson, 2001; Berry and Cooper, 1999).
Some researchers counter the suggestion that variety impacts performance negatively (Schonberger, 1986). Kekre and Srinivasan (1990) analysed a product information database and found no strong negative operational impact resulting from PV. Suarez et al. (1996) found similar results of a circuit board manufacturer, showing that increased equipment flexibility and PV did not lead to increased costs or decreased quality. Other studies have shown mixed results on the relationship between more detailed component variety measures and productivity measures in the automotive context (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996).

![Diagram of Moderating Factors affecting the relationship between Product Variety and Operational Performance]

**Figure 2-2** Moderating factors affecting the relationship between product variety and operational performance

A diverse set of moderating variables affecting the PV→OP relationships identified in the literature is shown in Figure 2-2. Moderating variables are variables that affect the size, direction or strength of a relationship between X and Y (Hayes, 2013). Product architecture and design is one such variable that determines a firm’s ability to compete operationally while producing the product offering (Fisher et al., 1999; Pine, 1993). If a firm offers largely homogenous products or employs a modular product architecture to variegate the products, synergies can be found within a product offering, which enable a firm to maintain economies of scale (Ramdas, 2003; Salvador et al., 2002). Other operational strategies, such as placing a buffer capacity at a bottleneck of resources to absorb the PV-induced variations in demand (Fisher and Ittner, 1999), regulating production planning and stocking decisions (Berry and Cooper, 1999; Pil and Holweg, 2004) and adjusting the customer order decoupling point through postponement (Davila and Wouters, 2007; Forza et al., 2008; Trentin and Forza, 2010), are tactics manufacturers can use to cope with variety without decreasing performance.
Regarding mediating variables, or variables that explain the mechanism through which X affects Y (Hayes, 2013), demand variation repeatedly appears in the PV management literature (Gottfredson and Aspinall, 2009; Jacobs and Swink, 2011; Ramdas, 2003). Increasing PV is related to increased volatility in demand for end items as the same consumer demand is spread out across more individual products. This volatility can reduce the accuracy of forecasts, thus causing mismatches between supply and demand, which then result in lost orders and scrapped inventory (Gottfredson and Aspinall, 2009; Ramdas, 2003).

One of the enablers of variety in a production context is the flexibility of the equipment. Gerwin (1987) describes seven types of flexibility: product-mix, changeover, modification, rerouting, volume, material and sequencing flexibility. One of the most commonly discussed types of flexibility in recent literature is product-mix flexibility (Bengtsson and Olhager, 2002; Berry and Cooper, 1999; Salvador et al., 2007; Slack, 1983; Wilson and Ali, 2014), which is defined as a production system’s ability to produce multiple product lines and variants within a product line (Gerwin, 1993; Slack, 1983) with low changeover costs (Berry and Cooper, 1999). The value of mix flexibility has been shown to decrease with increased demand volatility (Bengtsson and Olhager, 2002). Product-mix flexibility is influenced by product design, production scheduling, process technology and workforce training (Gerwin, 1987; Slack, 1983). Some methods that can increase the product-mix flexibility of an existing production line are workforce training (e.g. cross training, job rotation) and redesigning equipment to rapidly transition between different product types. Current research on reconfigurable production systems, or the form of process modularity, shows new ways of achieving mix flexibility through the physical reconfiguration of equipment, material handling systems, robots and fixtures (ElMaraghy et al., 2013; Patel and Jayaram, 2014).

As manufacturing lines are typically intentionally designed to produce a specific product range, the resulting lines have inbuilt flexibilities required to produce the desired products. This was concluded by researchers who analysed the effect of car model mix complexity on performance, and it appeared there was no effect because the line was designed to handle the required variety (MacDuffie et al., 1996).

### 2.4 Frameworks for Managing Product Variety

Effectively managing variety has been shown to be key to competitive advantage (Götzfried, 2013; Ramdas, 2003). There is no one dominant strategy for determining how to effectively and competitively manage variety (Ulrich, 2006), but the task typically involves balancing the need to meet market demand while maintaining scale economies in the value chain (Lancaster, 1990). Frameworks and methods for managing variety incorporating both marketing and operational perspectives have been published in academic and practitioner literature (Götzfried, 2013; Mariotti, 2008; Perumal and Wilson, 2017; Silveira, 1998; Wilson and Perumal, 2009). Three of the frameworks are discussed in detail, and other aspects of managing variety discussed in the literature are presented.
The framework by Silveira (1998) (see Figure 2-3) shows the importance of alignment between the general business strategy and the operations strategy of a company. The four steps of the framework guide a firm in discussing (1) the strategic importance of variety, (2) the OP desired at the firm, (3) the gap between business strategy and operations strategy and (4) which strategies to use to cope with PV. Silveira (1998) divides strategies for coping with variety into two categories: adaptive strategies, which proactively control variety, and flexibility strategies, which enable the more efficient production and delivery of variety. The framework was developed based on the literature and the experiences of five case companies in both Britain and Brazil.

Figure 2-3 Silveira's framework for managing product variety, adapted from Silveira (1998)

The second framework was created by Hvam et al. (2019) to aid companies in the reduction of product and process complexity through the calculation of complexity costs (i.e. costs that vary based on the product, but are not identified or allocated to products in traditional product costing methods) (Götzfried, 2013; Hansen et al., 2012; Hvam et al., 2019; Ramdas, 2003; Wilson and Perumal, 2009). Methods such as Activity-Based Costing (ABC) have been developed to better allocate overhead costs to individual products so that the profits of low-volume products are not overstated (Cooper and Kaplan, 1988). General steps for ABC include identifying expensive resources, for which consumption varies between individual products, and focusing on resources with unclear relationships to traditional cost allocation measures, such as processing time, direct labour, etc. (Cooper and Kaplan, 1988). With a focus on complexity costs, the framework by Hvam et al. (2019) consists of five steps:

1. Defining which products and processes to include in the analysis;
2. Grouping products into A, B and C categories based on a double Pareto analysis of their sales and contribution profit figures;
3. Identifying and quantifying the most important complexity cost factors;
4. Identifying short-term, medium-term and long-term initiatives to reduce complexity costs and quantifying possible cost savings;

5. Evaluating and prioritising complexity reduction initiatives.

The five-step framework heavily relies on the availability and accuracy of cost data within the firm and advocates for a more comprehensive allocation of costs at the product level to determine which products bring profit to the firm (Hvam et al., 2019). Its flexible five-step approach allows the framework to be applied to a variety of industrial contexts, and the article presents an example of applying the framework for a mechanical consumer products manufacturer.

The third framework, shown in Figure 2-4, is more specific to high-volume manufacturers in the process industry because it focuses on aligning the marketing strategy with the production process choice of low-volume or high-volume production (Berry and Cooper, 1999). The framework arises alongside the discussion of a high-volume plastics company, which increased PV and subsequently gained 20% additional sales revenue, but consequently, production batch sizes decreased by 50% and overall profits by 83%, indicating a mismatch in marketing and manufacturing strategy (Berry and Cooper, 1999). On the vertical axis of the framework, market price sensitivity indicates the customers’ willingness to pay more for additional productivity due to the company’s brand or the perceived value of the products (‘low’ indicating that customers are very willing and ‘high’ indicating otherwise). The horizontal axis shows the current or potential future production capabilities regarding efficient batch sizes. If a company faces the decision regarding whether to increase PV, Case (1) is the easiest to support because the higher prices paid by customers would result in attractive margins for the current, low-volume and flexible production process; however, Case (4) is the most difficult to support because the current technology does not support the low-volume batches typically required with increased PV. In addition, the customers are unwilling to pay the higher prices, which might offset the reduced efficiency of manufacturing.

![Figure 2-4 Framework for determining the business case for increased product variety, adapted from Berry and Cooper (1999)](image-url)
In addition to the three presented frameworks, further insights into effective PV management can be gained from the literature. Götzfried (2013) identifies four mechanisms for managing complexity in a product assortment: transparency on product portfolio and product complexity, transparency on value-chain process complexity, process redesign for decision making regarding products and reasoning in decision making involving products. He then combined these four factors into a cyclic framework driven by transparency on complexity to drive management decisions on the product portfolio. Ramdas (2003) also stresses the importance of decision making, which can occur because of organisational inertia, past decisions, ad hoc criteria or rational decision making. She describes how organisations must create and implement variety by deciding on the types of variety, product architecture, degree of customisation and timing of variety decisions while also determining the process capabilities, points of variegation and other daily order-fulfilment decisions.

Organisational competences also aid in the management of complexity. One study showed that organisations with a product-technology portfolio strategy, organisation and governance of PV decisions, organisational target setting and decision support systems used to aid product design all supported better product portfolio decisions (Closs et al., 2008). Organisational learning is also discussed as a competence that enables better variety management (Jacobs and Swink, 2011).

The subject of PV optimisation also arises in the literature as researchers seek to balance revenue, which decreases at a diminishing rate, with the rising costs that incur as PV is added (Bryan et al., 2007; Gottfredson and Aspinall, 2009; De Groote, 1994; Scavarda et al., 2009; Wilson and Perumal, 2009). Smith and Escobar-Saldivar (2006) present a mixed integer programme used to optimise the number of paint types and colours offered at a painted sheet metal manufacturer with the objective of maximising sales and margins and minimising inventory and setup costs. Other models optimise variety by using the margin per hour generated on bottleneck resources to decide which products to keep in the portfolio in accordance with the Theory of Constraints approach (Goldratt, 1984).

2.5 SUMMARY AND IDENTIFIED RESEARCH GAPS

PV and PV management are highly researched subjects both from academic and practitioner vantage points. The relationship between PV and OP is explored widely and is often discussed as being a negative relationship, but consensus on this fact is not clear due to contradictory literature findings (Kekre and Srinivasan, 1990; Ramdas, 2003). Considering the wealth of empirical studies on PV and OP, academic knowledge is lacking a structured synthesis of literature studies that provide information regarding which OP measures are most negatively affected by PV. In addition, many of the studies on PV and OP are carried out for automotive manufacturers, which have a high variety with many customisable options (Fisher and Ittner, 1999; Holweg and Pil, 2005; Ittner and MacDuffie, 1995; MacDuffie et al., 1996; Pil and
Holweg, 2004). A modest amount of work has been carried out in relation to process manufacturers (Berry and Cooper, 1999; Silveira, 1998), but these studies focus on typical process industry firms that adopt product and process structures found in the diagonal of the product-process matrix with no specific analysis of the effect of PV on process industry firms that produce a high variety of products in small production batches.

The PV management frameworks and approaches found in the literature utilise general terms that increase the applicability of such frameworks to a wide range of companies; however, such generalisation is void of the nuance required to meet the needs of individual industries and manufacturing settings. This is particularly the case for process industries that differ drastically from discrete industries in which approaches such as mass customisation (Pine, 1993) and Lean manufacturing (Shingo, 1989) have catalysed PV management initiatives. Contextual factors of the manifestation of PV in process industries that differ from those of discrete industries, including lower PC, higher process complexity, equipment flexibility, sequence-dependent setup times and low product prices, all support the use of adapted PV management techniques for process industries. Researchers have also argued that process industries require adapted approaches to methods such as Lean manufacturing (Abdulmalek et al., 2006; King, 2009) and Total Productive Maintenance (Chan et al., 2005), indicating the potential need for adapted PV management approaches as well. While one PV management framework found in the literature is tailored to the process industry (Berry and Cooper, 1999), this single example is hardly comprehensive in its reach and fails to address the many facets and methods of coping with increased variety.

For the reasons stated, it is argued that (1) further study of the relationship between PV and OP is required, particularly within process industry firms falling off the diagonal of the product-process matrix, (2) the impact of PV on OP should be quantified for these process industry firms and (3) methods for managing PV and enabling the efficient production of PV should be identified and/or developed and tested in process industry settings.
3 RESEARCH DESIGN

‘If you can introduce a topic to someone in a form that is digestible, then they can start adding back the nuance. We can have a conversation, and we can start talking about the complexity, but you’ve got to start the conversation. My job, the way I see it, is to start the conversation’. - Malcolm Gladwell

To begin the layered conversation regarding the effects of PV in process manufacturing firms, a structured research design is presented in the following sections. This work aims to contribute to the knowledge within OM literature regarding PV’s impact on OP, the magnitude of its impact and the methods that can be used to manage its impact in a process industry setting. The purpose of this research was to both test existing PV management theory and to build new extensions of this theory with respect to the process industry in the OM literature, making this research both explanatory and exploratory. The study of OM is a broad research domain covering the general strategy for operations, or the transformation of inputs (e.g. materials) to outputs (i.e. products), in relation to the broader business context (Karlsson, 2009).

3.1 PHILOSOPHICAL POSITION OF THIS THESIS

This thesis adopts a positivist research paradigm, known as the rational or objective paradigm, which is based on the belief of an objective reality that can be observed and measured. The opposite is a constructivist paradigm, which purports that all observations and analyses are socially constructed and dependent on the individual researcher (Croom, 2009). The paradigm of this thesis is positivist because the primary aim of the work is to discover objective facts, and the perspective of human actors involved in the project is only marginally discussed. The researcher assumes that the phenomenon of PV management can be assessed objectively within its context and that facts and observations can be used to explain its operation, evolution and success within industrial organisations (Meredith et al., 1989).

3.2 RESEARCH METHOD

The dominant research method characterising the PhD project is a mixed methods approach as presented by Creswell (2014). Mixed methods research is characterised by the systematic convergence of both qualitative and quantitative analyses performed either in parallel or in series (Creswell, 2014). While the number of scholars specifically citing a mixed methods approach is limited in recent OM literature (Dubey et al., 2015), researchers and editors from leading OM journals argue that more instances of mixed-methods research should be utilised to make an effective contribution in the heavily applied and dynamic field of OM (Boyer and Swink, 2008; Croom, 2009; Golicic and Davis, 2012; Taylor and Taylor, 2009). Benefits of multimethod research are improved triangulation due to the presence of multiple forms of evidence and the opportunity for more creative and divergent perspectives to arise on a topic (Eisenhardt, 1989; Mingers, 2001). Furthermore, large research programmes, such as a PhD project, provide ample opportunities for investigating an issue or phenomena through the lens of a combination
of multiple research methods (Mingers, 2001). Recent studies have shown that a mixed methods approach can be successfully applied in the supply chain context (Aslan et al., 2015; Dubey et al., 2015), thus suggesting that it is appropriate for investigating the dynamic and cross-functional area of PV management.

One of the arguments against the use of mixed methods research is that different research methods often align more closely with different research paradigms, which may be incompatible, a consequence referred to as paradigm incommensurability (Mingers, 2001). For example, case research is often discussed as a method within the constructivist research paradigm where truth is assessed through the lens of a subject’s experience, while quantitative modelling is often applied with a more positivist, objective view of truth (Croom, 2009); however, Mingers (2001) and Croom (2009) argue that it is possible to disconnect a method from its paradigm and to consciously use it within a less traditional paradigm. For example, interviews can be used to collect qualitative data within a positivist study by structuring the interview questions to address specific concepts, rather than using unstructured interview techniques (Meredith et al., 1989). The aim of this thesis and the studies contained within involves performing case studies and quantitative analyses within a positivist research paradigm.

Mixed methods techniques are applied in five of the eight studies within this thesis (see Table 3-1), which combine empirical case research with empirical statistical research, such as multiple linear regression and operations research (OR) (Wacker, 1998). Studies D and F do not explicitly state that multiple methods are utilised to answer their respective research questions, but it can be argued that these studies are examples of mixed methods research because they systematically integrate qualitative and quantitative analyses.

This thesis uses a multiphase mixed methods design, as depicted in Figure 3-1 (Creswell, 2014), allowing for the depth and analytical strength of quantitative methods to be combined with the richness of case studies. The methods are selected to appropriately address the needs of each research question. First, RQ1 is a ‘how’ question, which prompts a study of existing case literature as well as further case-based research (Tranfield et al., 2003; Yin, 2018). Second, RQ2 is a ‘what’ and ‘how much’ question related to assessing a relationship’s magnitude in a specific industry, thus motivating a predominantly quantitative study in tandem with case-based research to acquire contextual information from process industry settings (Creswell, 2014; Yin, 2018). Finally, RQ3 is a ‘what’ question, which can be answered using exploratory case-based research (Yin, 2018).
Table 3-1 Research methods used in this thesis

<table>
<thead>
<tr>
<th>RQ</th>
<th>Study</th>
<th>Title</th>
<th>Method</th>
<th>Method Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>RQ1</td>
<td>Study A</td>
<td>Product variety, product complexity and operational performance: a systematic literature review</td>
<td>Systematic literature review</td>
<td>Lack of systematic review and synthesis of existing literature</td>
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<tr>
<td></td>
<td>Study B</td>
<td>Product complexity and operational performance: a systematic literature review</td>
<td>Systematic literature review</td>
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<td>RQ2</td>
<td>Study C</td>
<td>Operational impact of product variety in the process industry</td>
<td>Mixed methods</td>
<td>Interview data informed model building</td>
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<td></td>
<td>Study D</td>
<td>Which variety is free? Discerning the impact of product variety in the process industry</td>
<td>Mixed methods</td>
<td>Interview data informed model building</td>
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<tr>
<td></td>
<td>Study E</td>
<td>Why slow down? Factors affecting speed loss in process manufacturing</td>
<td>Mixed methods</td>
<td>Interviews and free-text data informed model building; free-text data merged with quantitative data for analysis</td>
</tr>
<tr>
<td>RQ3</td>
<td>Study F</td>
<td>Product portfolio optimisation based on substitution</td>
<td>Mixed methods</td>
<td>Interviews informed model parameters; human performance compared to model performance</td>
</tr>
<tr>
<td></td>
<td>Study G</td>
<td>Framework for analysing speed losses in process manufacturing firms</td>
<td>Case study</td>
<td>Process industry manufacturer selected for testing a framework</td>
</tr>
<tr>
<td></td>
<td>Study H</td>
<td>Product wheels for scheduling in the baking industry: a case study</td>
<td>Mixed methods</td>
<td>Interviews and process analysis integrated with statistics and simulations</td>
</tr>
</tbody>
</table>

Phase 1 (RQ1) → Informs → Phase 2 (RQ2) → Informs → Phase 3 (RQ3)

Figure 3-1 Multiphase mixed methods research approach

As OM research has a strongly applied nature and history (Croom, 2009; Meredith et al., 1989), case studies are employed as one of the primary methods within this mixed methods study. Case studies allow researchers to observe phenomena in their natural settings to understand the dynamics of an individual setting and to utilise both qualitative and quantitative analyses to develop or to test a theory (Eisenhardt, 1989).

A quantitative analysis typically adopts a deductive approach to test hypotheses, which contributes to the knowledge related to certain issues. The analysis is typically evaluated based on its adherence to a scientific approach and its replicability, and the findings are interpreted based on statistical significance (Croom, 2009). The quantitative technique of OR has been widely
used in operations applications after transitioning from its military roots (Meredith et al., 1989), while descriptive analytical modelling (i.e. linear regression models) is used to mathematically describe how real-world systems work (Meredith et al., 1989).

Seven cases from two companies were analysed across the eight studies within this thesis. Each of the cases was consciously selected rather than randomly sampled to ensure that relevant process industry characteristics were displayed in the production systems and that data required to answer the research questions were available (Eisenhardt, 1989). This adds to the validity of the research presented. The unit of analysis employed in the studies for RQ2 and RQ3 was the individual production line when examining OP (see Studies C-E, G and H) and an individual business unit when analysing financial performance (see Study F). Individual production lines were most frequently studied due to the operational position of this thesis. Examining a single production line allows for the exploration of phenomena in isolated scenarios, limiting the effects of different capacities and product mixes and allowing the results to be compared across similar production lines. Single case studies have primarily been utilised in the studies contained in this thesis; however, six of the seven cases examined are from different production or sales entities within the same company, which is explained in Section 3.3. The primary data collection methods utilised for this thesis include archival analyses of production data, observations of the physical production systems and semi-structured interviews with production personnel and managers. The researcher visited six of the seven case companies in person to collect observations for the studies. Generalisability is achieved through the relevance of the case studies, as the cases selected were process industry manufacturers producing a high level of PV, aligning with the research questions.

In addition to the eight studies, this thesis also presents business insights from a longitudinal case of PV reduction at a manufacturing company. Documenting the initiatives implemented and their impact in a real-life industrial context was deemed relevant for inclusion in the report because this research was carried out as an industrial PhD project in collaboration with the manufacturing company in question. The researcher had access to sales and production data at the company from the past 3.5 years and access to people working with PV management, providing the opportunity to perform a longitudinal study. PV reduction was followed by the researcher at monthly and quarterly intervals from 2016 through 2018.

The researcher acknowledges that other methods could have been utilised to conduct the research project, such as design science research (DSR) (Vaishnavi and Kuechler Jr., 2008) or action research (Coughlan and Coghlan, 2009; Zuber-Skerritt and Perry, 2002); however, DSR was eliminated as a possible methodology because the research questions in this study do not lend themselves to be answered through the iterative design of a novel artefact as prescribed by the method. Similarly, action research was eliminated as a possibility because this study focuses on identifying and quantifying the effects of PV on performance rather than on the learning process of the organisation regarding PV management.
Researcher bias must also be considered when examining the design of the PhD project and the analysis of the results. Due to the large number of stakeholders, supervisors and company representatives involved, subjectivity may have affected the study. To overcome this, the research was presented in conferences and doctoral seminars and was submitted to journals to obtain external feedback from other experts in OM to improve the validity and rigor of the research.

3.3 PRIMARY CASE COMPANY: THE INSULATION COMPANY

The case studies and quantitative analyses performed for this thesis were largely accomplished through collaboration with a global producer of insulation materials for the building sector (see Studies C, D, E, F and G). The company has over 10,000 employees, over 20 factories and over 40 insulation production lines worldwide. Hereafter, the company is referred to as the insulation company.

While the exact factories and business units analysed for each study differ, the production process examined for each factory is nearly identical. A diagram showing the principle production process in each case involving an insulation manufacturer is provided in Figure 3-2. First, a mixture of raw materials is melted and poured onto a set of spinners, which blow the molten material into fibres, similar to a cotton candy machine. The fibres are collected, sprayed with adhesive and layered onto a conveyor belt, which transports the material through various pressing and forming processes to obtain the needed physical properties of the product. The product then passes through a curing oven to set the adhesive. Lastly, the cured product is discretised through a set of cutting operations and packed based on customer specifications.

![Figure 3-2 Insulation production process, adapted from Trattner, Hvam, Haug, et al. (2019)](image-url)
The insulation production process is an energy-intensive process that runs continuously 24 hours per day, seven days per week in many factories. Production is stopped only for periodic maintenance and major product changeovers. Each production run is dedicated to making only one specific stock keeping unit (SKU), which is a unique combination of packaging and thermal, mechanical and dimensional properties. Minor product changeovers are performed during production on the line by rejecting off-spec product downstream. The off-spec product is then granulated into fibres again and reused in upstream processes for certain products.

The insulation process is characterised as a hybrid production system consisting of an upstream continuous flow production section and a downstream connected line flow production section, which transforms the insulation material into discrete products (Hayes and Wheelwright, 1979). The speed and throughput of the line is regulated by operators based on product requirements. This case is unique because the continuous portion of the production line is tightly coupled to the discrete assembly line section of the line. Due to the tight coupling and lack of buffer inventory between processing stages, the speed of upstream and downstream processes must be synchronised continuously. If a specific product requires a machine downstream to run at a lower speed, then the upstream processes must be slowed down to prevent overloading the downstream machine. Because of the tight coupling of the continuous and discrete sections of the production line, the insulation company provides an interesting research context within the process industry.

More information regarding the insulation company in relation to PV management is presented in the Section 7, which details the methods used and the results produced from a three-year PV reduction project at the company.
4 How does product variety impact operational performance in industrial companies?

‘Productivity isn’t everything, but in the long run, it is almost everything. A country’s ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker’. - Paul Krugman, Nobel Prize Laureate

Productivity is one pillar of OP that is well-regarded as an indicator of societal progress. Understanding the variables that impact productivity and other OP measures is therefore not only of interest to individual firms attempting to increase revenues and profits but also of interest to society at large. PV has long been touted an enemy of OP, with authors citing key empirical works that demonstrate this assertion, but the literature lacks a synthesis of the empirical work done in this area to fully confirm and to extend OM theory. To obtain a broad view of the impact of PV on OP measures, two systematic literature reviews were conducted in Studies A and B (see Appendix for full texts) to synthesise existing empirical studies on the relationships between PV and four OP measures: cost, time, quality and delivery.

As Study B presents a refined and more comprehensive version of Study A, including an expanded scope to include more articles in the analysis, the results from Study B are presented here. The search strings and article screening results can be viewed in Table 4-1 and Figure 4-1, respectively. The search strings were used to query the Scopus and Web of Science databases for relevant articles. Previous systematic literature reviews in OM have demonstrated these to be comprehensive sources for peer-reviewed academic content (Costa et al., 2018; Suzić et al., 2018).

In Study B, over 3000 articles were gathered from the two databases, and 93 articles were included in the final sample. Most of these articles were published in OM journals, such as International Journal of Production Research and International Journal of Operations and Production Management. An average of two papers were published per year from 1992-2006, and an average of four papers were published per year from 2007-2017.

Both PV and PC measures were identified in the final literature sample but are grouped under the umbrella term of PC to simplify the discussion. Articles discussing the OP of both manufacturing and supply chain firms are included in the analysis, while the OP of service companies is excluded to limit the scope. Relationships between PC and OP were identified using the respective sub-measures of PC and OP to add richness to the findings.
Table 4-1 Article search strings by database, from Trattner, Hvam, Forza, et al. (2019)

<table>
<thead>
<tr>
<th>Database</th>
<th>Search String</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scopus (Elsevier)</td>
<td>(TITLE-ABS-KEY (“product complexity” OR “product vari*” OR “product diversi*” OR “product proliferation” OR “product portfolio complexity” OR “product customi*” OR “product scope” OR “product hetero*” OR “product mix”)) AND TITLE-ABS-KEY (“performance” OR “time” OR “speed” OR “delivery” OR “dependability” OR “quality” OR “defect” OR “scrap” OR “rework” OR “reliability” OR “flexibility” OR “productivity” OR “throughput” OR “efficiency” OR “cost” OR “inventory turn*”)) AND LANGUAGE (English) AND DOCTYPE (ar) AND PUBYEAR &gt; 1991 AND TITLE-ABS-KEY (“production” OR “manufactur*” OR “operation*”) AND (LIMIT-TO (SRCTYPE, “j”))</td>
</tr>
<tr>
<td>Web of Science (Thomson Reuters)</td>
<td>(TS=(“product complexity” OR “product vari*” OR “product diversi*” OR “product proliferation” OR “product portfolio complexity” OR “product customi*” OR “product scope” OR “product hetero*” OR “product mix”)) AND TS=(“performance” OR “time” OR “speed” OR “delivery” OR “dependability” OR “quality” OR “defect” OR “scrap” OR “rework” OR “reliability” OR “flexibility” OR “productivity” OR “throughput” OR “efficiency” OR “cost” OR “inventory turn”)) AND TS=(“production” OR “manufactur*” OR “operation*”))</td>
</tr>
</tbody>
</table>

Additional filters applied: LANGUAGE: (English) AND DOCUMENT TYPES: (Article) AND [excluding] DOCUMENT TYPES: (PROCEEDINGS PAPER), Timespan: 1992–2018

Figure 4-1 Article screening results, from Trattner, Hvam, Forza, et al. (2019)

Measures of PC were coded by the researchers into five respective sub-measures, which are defined in the list provided in the order of frequency of occurrence. Structural PC measures are most often utilised in the literature sample, which may be due to their simplicity and ease of data collection. Demand distribution measures are included because some authors argue that
the variation in demand across a set of products has a greater influence on OP than the number of products (Akkerman and van Donk, 2009; Fisher and Ittner, 1999).

- **Structural measures**: the absolute number of products, SKUs, components, product families, platforms or common components (Appelqvist et al., 2013; Bozarth et al., 2009; Koh et al., 2005; Moreno and Terwiesch, 2017; Novak and Eppinger, 2001; Pil and Holweg, 2004; Wan et al., 2012).

- **Composite measures**: a group of PC measures that incorporate multiple structural PC measures (e.g. number of items on the bill of material, number of engines) and production measures (e.g. manufacturing cost) into a customised equation for a specific manufacturing context (Anderson, 1995; Caniato and Größler, 2015; Fisher and Ittner, 1999; Hegde et al., 2005; Ittner and MacDuffie, 1995; Vilas and Vandaele, 2002).

- **Product mix skewness**: a group of PC measures representing the skewness in demand across products in a factory or product portfolio (e.g. Herfindahl index and entropy index) (Akkerman and van Donk, 2007, 2009; Brahm et al., 2017; Vachon and Klassen, 2002).

- **Degree of customisation**: the level of customisation of the product or the degree to which customers are involved in the product development or production process (Ahmad and Shroeder, 2001; Bozarth et al., 2009; Xia and Rajagopalan, 2009).

- **Production measures**: a group of PC measures related to PC’s effects in production, including the batch size, number of setups and PV-induced manufacturing complexity (Anderson and Sedatole, 2013; Celano et al., 2012; Hu et al., 2008; Yang and Deane, 1993).

When reviewing each article in the final literature sample, PC→OP relationships were identified and categorised as negative if the increasing PC is detrimental to OP (i.e. rising costs, increasing lead times, lower quality and lower delivery reliability) and positive if it is beneficial to OP. If a quantitative analysis of the PC→OP relationship was performed, the linear, quadratic or logarithmic nature of the relationship was also documented.

### 4.1 INCREASED PRODUCT VARIETY IS PREDOMINANTLY RELATED TO DECREASED OPERATIONAL PERFORMANCE

The results of the analysis showed that PC measures have consistently negative relationships with measures of OP. Dominant relationships between PC and OP identified in the full-text screen are summarised in Table 4-2 to provide a concise overview of the findings. These relationships were largely found to be linear and unidirectional in nature (bi-directionality was not investigated), but evidence of an inverted U-shaped (Brahm et al., 2017; Wan, 2016; Wan and
Dresner, 2015) and U-shaped relationships was also found (Akkerman and van Donk, 2007; Brabazon et al., 2010; Van Den Broeke et al., 2015; Wan et al., 2012, 2014).

**Table 4-2 Relationships identified in full-text readings between product complexity and operational performance measures, from Trattner, Hvam, Forza, et al. (2019)**

<table>
<thead>
<tr>
<th>OP Measure</th>
<th>Positive relationship</th>
<th>No relationship</th>
<th>Negative relationship</th>
<th>U-shape</th>
<th>Inverted U-shape</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Costs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operations costs (general)</td>
<td>1</td>
<td>4</td>
<td>16</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Direct labour costs</td>
<td>1</td>
<td>5</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufacturing overhead costs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inventory costs</td>
<td>1</td>
<td>2</td>
<td>12</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lead time</td>
<td>1</td>
<td>4</td>
<td>14</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processing time</td>
<td>1</td>
<td>3</td>
<td>14</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Setup time</td>
<td></td>
<td></td>
<td></td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Productivity</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td><strong>Quality</strong></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td><strong>Delivery</strong></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

Most highly researched were the PC→cost and PC→time relationships, each with approximately 60 examples or incidents of quantitative testing in the literature. The PC→quality and PC→delivery relationships were studied less often, each with approximately 25 examples or incidents of quantitative testing. Many studies revealed either a lack of significance for the PC variables in relation to quality and delivery or a negative relationship between said variables, with no dominant relational direction surfacing.

The relationships are most clearly negative between structural PC measures, product mix skewness and production PC measures when related to cost and time performance. Studies utilising composite PC measures do not present a dominant relationship with any OP measures. A set of these studies have generated an array of composite PC measures to perform quantitative analyses in specific industrial contexts, such as automotive and flat glass manufacturers, with only a fraction of the PC measures proving to be statistically significant in relation to OP (Anderson, 1995; Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996). Using composite PC measures does allow the researcher flexibility in tailoring the analysis to each case, but it does not allow for generalisability.

Seven instances of a positive PC→OP relationship emerged from the literature study (Eckstein et al., 2015; Gupta and Srinivasan, 1998; MacDuffie et al., 1996; Moreno and Terwiesch, 2017; Ruiz-Torres and Mahmoodi, 2007; Tracey, 2004) of 167 instances identified in the total literature sample. Some of the studies offered no causal explanation for the findings (Eckstein et al., 2015; MacDuffie et al., 1996; Moreno and Terwiesch, 2017; Tracey, 2004). Other authors cited improved flexibility from cellular manufacturing (Ruiz-Torres and Mahmoodi, 2007) and
the standard adjustment of processing times after a PC increase (Gupta and Srinivasan, 1998) as causal explanations for the positive relationship.

In the following sections, the identified relationships between PC and each OP measure are presented and discussed.

4.1.1 Decreased Cost Performance
Study B revealed numerous articles supporting the claim that increased PC leads to increased manufacturing and supply chain costs and thus decreased cost performance. While most of these studies suggest a linear relationship between the number of finished products or product families produced and operations costs, two cases of an inverted U-shaped relationship (Wan, 2016; Wan and Dresner, 2015) and one case of a U-shaped relationship (Van Den Broeke et al., 2015) were also identified. The inverted U-shaped PC→cost relationship implies that costs will rise with increasing PC only to a specific point, after which the total costs will decrease, while a U-shaped relationship implies the opposite.

The primary mechanism involved in the increased operational costs associated with higher levels of PC is the additional coordination costs (or transaction costs) required throughout the value chain to ensure the right products are produced and delivered at an acceptable level of quality (Ahmad and Shroeder, 2001; Ittner and MacDuffie, 1995). Ittner and McDuffie (1995, p. 315) elucidate the operationalisation of coordination costs in the automotive sector and state that ‘with an increasingly complex product mix comes additional parts, greater inventory and material handling, additional setups, more complex scheduling and task assignment, and increased supervisory requirements’.

An additional PC→cost mechanism identified in the literature sample is the degree of similarity between products. One study of a beverage manufacturer shows that adding products that differ from the existing assortment will lead to a more detrimental impact on operational costs than adding products that are similar to the existing assortment (Wan, 2016); however, others show that adding products with greater similarity can also cause increased processing times and production costs as operators face greater choice complexity in production (Busogi et al., 2017).

The relationship between PC and inventory costs is clearly negative and predominantly linear, though one instance of a U-shaped relationship was found (Brabazon et al., 2010). The relationship possesses two logical mechanisms: (1) if a firm uses an MTS strategy and simultaneously increases PV, the amount of stock will likely increase, thus increasing inventory costs, and (2) if a firm increases PC, forecasting accuracy decreases, leading to greater scrapped inventory and a loss of sales due to stock-outs (Wan and Sanders, 2017). Inventory costs can be managed with increasing PV by adjusting the stocking strategy (e.g. from MTS to MTO) or moving the customer-order-decoupling point upstream in the production process so that customisation is postponed and fewer finished variants are kept in stock (Pil and Holweg, 2004).
4.1.2 DECREASED TIME PERFORMANCE
The literature reveals a predominantly negative relationship between PC and time-related OP measures, including measures of lead time, processing time, setup time and productivity. The mechanism for the reduced time performance is similar to that of cost performance, namely the increase in coordination activities (also called operational friction) across the value chain and the customer order decoupling point (Brahm et al., 2017). Increasing the number of product variants in the value chain can cause complexity in production and distribution, increase the likelihood of errors due to an increased number of transactions and increased operator choice complexity, increase the risk of a disruption to the supply chain (e.g. a supplier’s failure to deliver critical components), create unplanned delays and increase the overall lead time to the customer (Busogi et al., 2017; Inman and Blumenfeld, 2014; Jacobs and Swink, 2011; Mapes et al., 1997). A high variation in production times across products as well as a high correlation of demand between products were also linked with increased lead time (Akkerman and van Donk, 2009; Vilas and Vandaele, 2002).

4.1.3 UNCLEAR RELATIONSHIPS WITH QUALITY AND DELIVERY PERFORMANCE
The PC→Quality and PC→Delivery performance relationships identified in the final literature sample are almost equally split between ‘no relationship’ and ‘negative relationship’ categorisations, indicating a lack of consensus among researchers in these areas. Despite the lack of clarity, it can be concluded that there is a slight negative tendency in research studies investigating PC’s relationship with quality and delivery performance.

The primary mechanism suspected to govern the cases of a negative impact of PC on quality measures (e.g. rework percentage, error rate, inspection costs) and delivery measures (e.g. responsiveness, order fill rate) is the coordination activities within the value chain. Studies show that higher PC levels can impede operational focus, resulting in more manufacturing errors, delivery errors, order mismatches and rework as well as more decisions to be made with internal and external supply chain stakeholders (Ahmad and Shroeder, 2001; Mapes et al., 1997; Shah et al., 2017). Demand uncertainty (Koh et al., 2005) and the dissimilarity between products (Wan et al., 2012) are also mentioned as mechanisms underlying the PC→Delivery relationship. The studies that show no relationship often include composite PC measures used in the analyses of survey results.

4.2 DEFICIENCY OF RESEARCH REGARDING PROCESS INDUSTRIES
An industry analysis was also conducted in Study B to identify the types of companies that are more commonly studied for PC→OP relationships. The results, which are provided in Table 4-3, show that companies producing transport equipment and electronics are the most often studied for the impact of PC on OP. Food and beverage companies are also studied with a
relatively high frequency. Many of the case companies represented in Table 4.3 primarily utilise assembly or machining operations to produce goods, while process industry manufacturers that produce goods using continuous flow or batch processes receive moderate to low coverage in the literature.

Table 4.3 Article case examples by industry code, from Trattner, Hvam, Forza, et al. (2019)

<table>
<thead>
<tr>
<th>SIC Code (two-digit)</th>
<th>Production System</th>
<th># of Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>37</td>
<td>Assembly line</td>
<td>21</td>
</tr>
<tr>
<td>36</td>
<td>Assembly line</td>
<td>10</td>
</tr>
<tr>
<td>20</td>
<td>Continuous &amp; batch</td>
<td>9</td>
</tr>
<tr>
<td>23</td>
<td>Batch production</td>
<td>3</td>
</tr>
<tr>
<td>35</td>
<td>Assembly line</td>
<td>3</td>
</tr>
<tr>
<td>28</td>
<td>Continuous &amp; batch</td>
<td>2</td>
</tr>
<tr>
<td>31</td>
<td>Batch production</td>
<td>2</td>
</tr>
<tr>
<td>34</td>
<td>Manufacturing cells</td>
<td>2</td>
</tr>
<tr>
<td>22</td>
<td>Batch production</td>
<td>1</td>
</tr>
<tr>
<td>32</td>
<td>Continuous</td>
<td>1</td>
</tr>
<tr>
<td>33</td>
<td>Continuous</td>
<td>1</td>
</tr>
<tr>
<td>39</td>
<td>Batch production</td>
<td>1</td>
</tr>
<tr>
<td>47</td>
<td>N/A</td>
<td>1</td>
</tr>
<tr>
<td>50</td>
<td>Assembly line</td>
<td>1</td>
</tr>
<tr>
<td>59</td>
<td>Assembly line</td>
<td>1</td>
</tr>
<tr>
<td>Mixed</td>
<td>N/A</td>
<td>18</td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>22</td>
</tr>
</tbody>
</table>

Note: an article may appear more than once in this list, therefore the sum is > 93 articles.

Among the studies of PC’s impact on productivity, there is a 70% agreement among authors that the effect of PC on productivity is negative, but only one of the studies specifically considers a firm in the process industry (Berry and Cooper, 1999). This single study focuses on a high-volume chemical company that produces 500 products in total, but the quantitative analysis of the PV→productivity relationship only assesses 16 representative products, which are made in very large batches (4 to 120 hours). There are situations in the process industry in which high PV induces the production of very small batches, much shorter than those of the chemical company, despite the rigidity of the equipment. This is a situation that may become more frequent as customisation and PV increase globally, and it is not yet been evaluated in literature.

The Hayes and Wheelwright’s (1979) product-process matrix (see Figure 1.1) shows that companies in the process industry are often located on the diagonal and produce both high-volume and standardised products on continuous flow production systems. The PV/PC→OP literature does not consider process industry firms with a high variety, high automation, completely integrated production systems or small batch sizes, such as at the insulation company studied in this thesis. High variety is viewed in some cases within the steel industry, but the variety-
producing discrete process is often decoupled from the continuous portion of the process (Denton et al., 2003). The insulation company examined in the following sections uses a process that is not decoupled, and automation is used all the way down the line. Due to the characterisation of the insulation company, this thesis has a unique research context by examining a firm that moves outside of the diagonal matrix of the product-process matrix and operates profitably. Also due to its characterisation, the productivity of the process at the insulation company is expected to experience a strong influence from setups and changeovers between batches.
5 What is the impact of product variety on process productivity?

 variability is a well-known and pervasive nuisance in the pursuit of operational excellence (Christensen et al., 2007; MacDuffie et al., 1996). Understanding the drivers of variability is not always straightforward, particularly within process industries in which many complex interactions occur between raw materials and equipment at extreme temperatures and pressures. With capital-intensive production processes, endless pressure to maximise equipment utilisation and throughput to reduce costs and the increasing demand for PV, firms in the process industry must understand the impact of PV on process variability to remain competitive.

The literature shows that increased PV typically manifests itself in process industry contexts through the more difficult production scheduling of fixed assets, increased changeovers and reduced run length (Fransoo, 1992). Sequencing between products is shown to be a relevant factor in process manufacturing contexts in which the product characteristics and performance of the previous batch may influence the current batch (Anderson and Sedatole, 2013). Determining ‘which variety is free’ has been the focus of MacDuffie et al. (1996) in their study on the impact of product features on labour productivity for automotive manufacturers, but a similar study has yet to be performed for a process manufacturing company.

This section presents a synthesis of Studies C, D and E, which aimed to quantify the magnitude of the impact of PV on OP, particularly on the process productivity (i.e. throughput) of insulation production lines (see Table 5-1 for an overview). Only the production phase of the value chain is assessed for the PV → OP impact due to the high cost of production in process industry companies (Fransoo, 1992). As this section presents only summaries of the three quantitative analyses, some technical details are left out for the sake of brevity. For full lists of technical stipulations for each of the three analyses, refer to the full-text articles in the Appendix.

The aim of Study C was to create an operational procedure by which production schedulers can combat the negative influence of PV on process productivity while applying the methodology used by Berry and Cooper (1999), who analyse the effects of batch size and sequencing on a set of process productivity measures at a chemical manufacturer. Study D, a short extended conference abstract, investigates the effect of product features and architecture on the process productivity of a different insulation manufacturing line with the purpose of determining ‘which variety is free’. The findings of Study D are elaborated on in Section 5.2. In Study E, the magnitude of the impact of PV on OP is assessed through the lens of Total Productive Maintenance (TPM) and lost production speed. Speed loss is one of the six major losses identifiable in production systems using the TPM approach popularised by Nakajima (1988) and is
measured as the difference between a machine’s designed production speed and actual production speed. Though PV is not explicitly mentioned in Study E, the impact of high PV could be said to affect scheduling-related variables, such as sequencing and run length, in the results.

Table 5-1 Summary of quantitative studies C-E

<table>
<thead>
<tr>
<th>Study C</th>
<th>Study D</th>
<th>Study E</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective</strong></td>
<td>Assess impact of PV on process productivity and create operational planning strategies to cope with PV</td>
<td>Assess the impact of individual features on process productivity</td>
</tr>
<tr>
<td><strong>Regression technique</strong></td>
<td>Ordinary least squares regression</td>
<td>Lasso regression</td>
</tr>
<tr>
<td><strong>Case data</strong></td>
<td>One insulation factory in Western Europe, one year of data at the batch level</td>
<td>One insulation factory in Eastern Europe, one year of data at the batch level</td>
</tr>
<tr>
<td><strong>Dependent variable</strong></td>
<td>Process productivity 1: tons of saleable output / (processing time + changeover time)</td>
<td>Process productivity 1: tons of saleable output / (processing time + changeover time)</td>
</tr>
<tr>
<td></td>
<td>Process productivity 2: tons of saleable output / processing time</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Process productivity 3: (expected processing time in sequence – actual processing time) / expected processing time in sequence</td>
<td></td>
</tr>
<tr>
<td><strong>Results</strong></td>
<td>Run length and sequence were statistically significant factors related to process productivity, with the effect varying based on product density</td>
<td>Some product features are related to reduced process productivity while others are ‘free’. Run length and sequence are significant control variables</td>
</tr>
</tbody>
</table>

Understanding the dependent variables presented in Table 5-1 and how they relate to the operation of the insulation lines is key to the interpretation of the results of this quantitative section. The insulation process illustrated in Figure 5-1 is designed with flexibility in certain production stages, which allow for quick, minor changeovers for certain product sequences and time-consuming major changeovers for other product sequences. Minor changeovers (e.g. products differing only in length or width) can be performed while insulation is being produced and can last between 0-4 minutes. The off-spec material that is generated during a minor changeover is diverted to a waste stream where it is granulated and recycled; however, major changeovers
(e.g. products greatly differing in thickness and/or density) can require a production stop where either (1) the conveyors on the line are paused to allow operators to physically adjust equipment or (2) production of fibres is stopped, and the entire production line is emptied of material to be filled again with a product of significantly different properties.

Figure 5-1 Insulation production process showing recycled waste loop, adapted from (Trattner and Hvam, 2018)

Figure 5-2 Time and volume measures of the insulation production process

Figure 5-2 illustrates how the different changeovers affect the time and volume measures and thus the process productivity measures of an insulation production line. As shown in Table 5-1, three measures of process productivity are used:

- **Process productivity 1**: \( \frac{\text{saleable product}}{\text{processing time} + \text{changeover time}} \) a measure of net output that includes the effects of changeover waste and any speed ramp-up of the production system;

- **Process productivity 2**: \( \frac{\text{saleable product}}{\text{processing time}} \) a measure of net output that includes only the effect of the speed ramp-up of the production system;

- **Process productivity 3**: \( \frac{\text{expected processing time in sequence} - \text{actual processing time}}{\text{expected processing time in sequence}} \) a measure of deviation in production speed that includes the effect of speed ramp-up and is normalised per product; and

- **Gross productivity**: \( \frac{\text{changeover waste} + \text{saleable product} + \text{other waste}}{\text{processing time} + \text{changeover time}} \) a measure that represents the total output rate per batch for the upstream, continuous part of the line.
The results show that PV impacts process productivity at the insulation company through shorter run lengths, more complex sequencing and the imposition of bottlenecks on the production line to achieve the specified product features. Short run lengths are related to 5-8% lost process productivity for over half of the product groups studied, and scheduling in a suboptimal sequence is related to 5-9% of lost process productivity depending on the run length for nearly all the product groups studied. Some product features are related to reduced process productivity, while others are found to be ‘free’, resulting in increased process productivity. Production bottlenecks caused by differing product architectures are accounted for across studies and are also shown to influence process productivity.

These findings are relevant to operations managers in the industry because they can be used to inform PV management decisions and business cases for variety extension or reduction. Regarding theory, Section 4 reveals that the effect of PV on performance has been widely tested in the automotive and electronics industries but has largely been neglected for process industries beyond food and beverage producers. These studies contribute to the limited amount of PV management literature targeting the process industry and allow for the true impact of PV to be assessed in relation to existing literature. As all analyses in this section were performed on similar production lines at the insulation company, the results from the three studies are comparable.

5.1 Impact of Product Variety via Production Planning and Scheduling

Across the four production lines analysed in Studies C-E, production planning and scheduling are the most consistently identifiable mechanisms through which PV impacts process productivity. Anecdotal evidence from the cases suggests the importance of strategic and tactical production planning in determining the PV-process productivity relationship because the manufacturing strategy of using a dedicated production line or a flexible all-purpose line is believed to affect the output of the machinery across the insulation factories observed. At the insulation company, more flexible lines producing greater PV often had lower relative process productivity than the dedicated lines that produced a narrow product range, which is a phenomenon discussed in the literature (Skinner, 1974). The decision regarding whether to use dedicated or flexible lines is often determined at the factory design stage before equipment is built (Fine and Hax, 1985); however, production planners must consider the manufacturing strategy and technological capabilities of each line in the operational phase of the factory as well to appropriately allocate new product variants to the existing lines.

Production scheduling factors, such as sequencing and run length, are also identified as having a relationship with OP in the four lines assessed in Studies C-E. It can be logically deduced that if a production line with unchanged capacity experiences an increase in PV, batch sizes and run lengths will become smaller. This phenomenon was observed in Study E when two lines in the same factory experienced different variety levels, one producing 229 products and
the other producing 481 products. The line producing a higher variety had run lengths that were on average half as long as the line with a lower variety.

In the following two sections, a refined and expanded version of Study C is presented, which quantifies the effects of sequence and run length on process productivity measures, and the results from Studies C-E are described in an integrative manner.

5.1.1 REFINEMENT OF STUDY C

The analysis of the impact of run length and sequence on process productivity on the single production line presented in Study C is refined and expanded in this section in the following ways:

- Because the different products have different production times per unit, the independent variable of run length \((X_1)\) is expressed as the expected processing time per batch, calculated as the weighted average processing time per kilogram multiplied by the batch size. The original study represents run length as the actual process time plus actual changeover time per batch.

- The independent variable representing the quality of production sequencing for a batch \((X_2)\) has been modified so that it equals 1 when the current batch is scheduled out of the best sequence, which minimises changeover waste, and it equals 0 when it is scheduled in the best sequence.

- While the previous model only tested the dependent variable process productivity 1, the analysis here is expanded to model process productivity 2 and process productivity 3 as well.

- The model tested has been changed from the form \(Y = B_0 + B_1 \ln(X_1) + B_2X_2\), where \(Y\) is process productivity 1, 2 or 3, \(X_1\) is the expected processing time and \(X_2\) is the sequencing variable, to \(Y = B_0 + B_1 \ln(X_1) + B_2 \frac{X_2}{X_1}\). This modelling change was made to represent the diminishing effect of an improper sequence with an increasing run length.

- More data points for each product family (PF) are included for analysis than in the original Study C, with an overview of descriptive statistics per PF shown in Table 5-2.

<table>
<thead>
<tr>
<th>Table 5-2 Production run characteristics for three product families (PFs) in the revision of Study C</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Production runs</strong></td>
</tr>
<tr>
<td>Production runs</td>
</tr>
<tr>
<td>Production runs out of sequence (# and % of production runs)</td>
</tr>
<tr>
<td>Products analysed</td>
</tr>
<tr>
<td>Average processing time (hours)</td>
</tr>
</tbody>
</table>
Plots of the regression results for process productivity 1, 2 and 3 are shown in Figure 5-3, Figure 5-4 and Figure 5-5, respectively. The coefficients and model fit for process productivity 1, 2, and 3 are shown in Table 5-3, Table 5-4 and Table 5-5, respectively.

![Figure 5-3 Model fit for process productivity 1 per batch for three product families (y-axis scale removed for confidentiality but standardised across charts)](image)

<table>
<thead>
<tr>
<th>Table 5-3 Regression results for process productivity 1 (intercept estimates removed for confidentiality)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Products</strong></td>
</tr>
<tr>
<td>Estimate</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
</tr>
<tr>
<td>Sequencing / Exp. Processing Time</td>
</tr>
<tr>
<td>Adjusted R squared</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Product Family 2</strong></th>
<th><strong>Product Family 3</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>Std. Error</td>
</tr>
<tr>
<td>----------</td>
<td>------------</td>
</tr>
<tr>
<td>Intercept</td>
<td>-</td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
<td>203.9</td>
</tr>
<tr>
<td>Sequencing / Exp. Processing Time</td>
<td>-41999.7</td>
</tr>
<tr>
<td>Adjusted R squared</td>
<td>0.156</td>
</tr>
</tbody>
</table>

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, """" p<0.1, """" p<1
Table 5-4 Regression results for process productivity 2 (intercept estimates removed for confidentiality)

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>P Value</th>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Products</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>Product Family 1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-115.1</td>
<td>&lt;0.001***</td>
<td></td>
<td>-176.6</td>
<td>&lt;0.001***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
<td>177.3</td>
<td>25.3</td>
<td>&lt;0.001***</td>
<td>475.1</td>
<td>37.2</td>
<td>&lt;0.001***</td>
<td></td>
</tr>
<tr>
<td>Sequencing / Exp. Process Time</td>
<td>-36521.8</td>
<td>2732.7</td>
<td>&lt;0.001***</td>
<td>-32849.6</td>
<td>4929.4</td>
<td>&lt;0.001***</td>
<td></td>
</tr>
<tr>
<td>Adjusted R squared</td>
<td>0.093</td>
<td></td>
<td></td>
<td>0.187</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Product Family 2</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>Product Family 3</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-257.4</td>
<td>&lt;0.001***</td>
<td></td>
<td>249.8</td>
<td>&lt;0.001***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
<td>71.7</td>
<td>70.13</td>
<td>0.307</td>
<td>267.5</td>
<td>50.7</td>
<td>&lt;0.001***</td>
<td></td>
</tr>
<tr>
<td>Sequencing / Exp. Process Time</td>
<td>-37885.2</td>
<td>4030.3</td>
<td>&lt;0.001***</td>
<td>-52812.4</td>
<td>7154.9</td>
<td>&lt;0.001***</td>
<td></td>
</tr>
<tr>
<td>Adjusted R squared</td>
<td>0.109</td>
<td></td>
<td></td>
<td>0.102</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, ** p<0.1, *** p<1
Figure 5.5 Model fit for process productivity 3 per batch for three product families

Table 5.5 Regression results for process productivity 3

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>P Value</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All Products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.058</td>
<td>0.010</td>
<td>&lt;0.001***</td>
<td>-0.105</td>
<td>0.017</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
<td>0.009</td>
<td>0.002</td>
<td>&lt;0.001***</td>
<td>0.017</td>
<td>0.004</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>Sequencing / Exp. Proc-</td>
<td>-2.789</td>
<td>0.247</td>
<td>&lt;0.001***</td>
<td>-2.899</td>
<td>0.487</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>essing Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R squared</td>
<td>0.059</td>
<td></td>
<td></td>
<td></td>
<td>0.060</td>
<td></td>
</tr>
<tr>
<td><strong>Product Family 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.022</td>
<td>0.022</td>
<td>0.318</td>
<td>-0.150</td>
<td>0.022</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>Ln (Exp. Process Time)</td>
<td>0.005</td>
<td>0.006</td>
<td>0.383</td>
<td>0.027</td>
<td>0.005</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>Sequencing / Exp. Proc-</td>
<td>-2.795</td>
<td>.344</td>
<td>&lt;0.001***</td>
<td>-3.621</td>
<td>0.637</td>
<td>&lt;0.001***</td>
</tr>
<tr>
<td>essing Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R squared</td>
<td>0.083</td>
<td></td>
<td></td>
<td></td>
<td>0.088</td>
<td></td>
</tr>
<tr>
<td><strong>Product Family 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Product Family 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance codes: *** p<0.001, ** p<0.01, * p<0.05, ." p<0.1, ." p<1
The first assessment showing process productivity 1 in Figure 5-3 shows the effect of the changeover time between products, the ramp-up in speed required when transitioning between products and the difference in productivity rates between products. Both the expected processing time and sequencing coefficients are statistically significant for all product families examined. The production runs that are scheduled in the ideal sequence have a higher process productivity than the batches scheduled out of the best sequence for batches running less than three hours, which is evidenced by the gap between the blue and the red lines in Figure 5-3. After three hours of process time, the effect of scheduling out of the best sequence diminishes as the blue and red lines converge. Due to the construction of the process productivity 1 variable, the sequence of production runs can be observed to be related to both the changeover waste between products and the ramp-up (or ramp-down) in speed required when changing between products on the insulation production line. It also appears that the productivity of the process converges to an asymptotic value as the expected processing time increases.

The analysis of process productivity 2 shows that the expected processing time and sequencing are statistically significant variables for almost all product families modelled. The only exception is PF2, where the processing time is not statistically significant, which could be due to the low production run lengths for this PF. The same convergence of process productivity is observed in Figure 5-4 as that of Figure 5-3. Because the process productivity 2 variable is designed to exclude the effects of changeover waste and changeover time (unlike process productivity 1), the logarithmic curves in Figure 5-4 are flatter than the curves in Figure 5-3. This difference is especially noticeable for product families 2 and 3. Even when excluding the impact of changeover waste in this analysis, the difference between the in sequence and out of sequence runs remains significant, indicating that sequencing also affects the process productivity through ramp-up and ramp-down activities across the three product families. The green and red curves in Figure 5-4 also appear to converge earlier than in Figure 5-3, indicating that the detrimental effect of sequencing on speed ramp-up is recovered sooner on the product line than the effect of sequencing on both speed ramp-up and changeover waste.

Across the analyses of process productivity 1 and 2, there is much higher variability for shorter processing times than for longer processing times. For product families 2 and 3, there is a clear discontinuity in the data set at around two hours of process time, with the batches over two hours being much more uniform in the process productivity than the batches less than two hours. Causes of the high variability for short production batches could be the variation in recycled waste material that is added to each production batch, differences in operator crews and the inherent productivity differences across the 100-150 products in each PF. An additional aspect that is evident across the two studies is that product families 2 and 3 appear to be more sensitive to sequencing than PF1, indicated by the large (or small) gap between in and out of sequence regression lines.

In the analysis of process productivity 3, the differences in production speed across products within each PF is normalised. The plots in Figure 5-5 show that batches of the same product can vary between 40% above and 60% below the average process productivity per product. It
was expected that normalising the data per product would result in a decrease in variability, particularly for the smaller batches, but this is not the case. High variability is still observed for smaller batches in Figure 5-5, indicating that there are other causes of variation in process productivity at play. Run length and sequencing variables are also significant for most product families, as indicated by the previous two analyses.

5.1.2 TRENDS ACROSS STUDIES C-E

Lower run lengths affect the process productivity, or throughput, of insulation production lines by giving operators less time to make changes to the process to achieve the mechanical and aesthetic properties of consecutive products in the production schedule. A slight increase in process productivity was identified as run lengths increased on over half of all product segments studied across four insulation production lines, but the increase appeared to diminish after 3-4 hours. A logarithmic relationship was found to best fit the relationship between run length and process productivity in Studies C and D, while a linear relationship is modelled in Study E. Study C presents a rather basic model accounting for only run length and sequencing variables. It is clear from the regression plots and the low R squared values in Study C that additional sources of variability are at play in the insulation process, particularly for short runs. The product segments with no relationship between run length and process productivity were found to be scheduled with average run lengths of less than two hours, where the variability in process productivity is higher. The pattern of decreasing variability in process productivity as run lengths increased is consistent across all four lines observed in this analysis and has been confirmed by the insulation company as a standard relationship across other production lines outside the scope of this study.

Table 5-6 Increase in process productivity for product family 1 by increasing run length, from Moseley et al. (2016)

<table>
<thead>
<tr>
<th>From run length:</th>
<th>0.5 hour</th>
<th>1 hour</th>
<th>1.5 hours</th>
<th>2 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25 hour</td>
<td>2%</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
</tr>
<tr>
<td>0.5 hour</td>
<td>-</td>
<td>2%</td>
<td>3%</td>
<td>4%</td>
</tr>
<tr>
<td>1 hour</td>
<td>-</td>
<td>-</td>
<td>1%</td>
<td>2%</td>
</tr>
<tr>
<td>1.5 hours</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1%</td>
</tr>
<tr>
<td>2 hours</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

The magnitude of the impact of production planning can be inferred from the results of the regression analysis in Studies C-E. An overview of the expected percentage increase in process time productivity by transitioning from a lower average run length to a higher average run length from the original Study C is provided in Table 5-6. Clearly, the largest increase in productivity occurs by increasing the products with runs lasting fifteen minutes to two hours, resulting in an estimated 6% increase in process productivity. On the line assessed in Study D, a similar increase in run lengths from fifteen minutes to two hours would result in a 5-8%
increase in process productivity based on the model coefficients and depending on the product segment. Study E did not reveal as large an increase in process productivity from increasing run lengths (<1% increase in process productivity when increasing run length by two hours), which might be explained by the inclusion of new process variables in the model that possess a higher explanatory power.

Sequencing also proved to be an important production scheduling parameter in relation to process productivity. As PV increases on a line, production scheduling becomes more complex as planners must consider greater demand variability at the product level and the additional sequencing possibilities, all while considering order due dates, last minute order changes and other factors affecting the production schedule.

The effect of suboptimal production scheduling at the insulation company is visible in Figure 5-3 and Figure 5-4, where the predicted process productivity takes the form of two lines, with the top line representing the predicted productivity for runs scheduled in the preferred sequence (i.e. the sequence that reduces changeover times and changeover waste) and the lower line representing the predicted productivity for the runs scheduled out of the preferred sequence. The product changes that qualify as being in the preferred sequence were determined through interviews with four production planners at the insulation company. The planners agreed on two rules: (1) that products with similar densities should be sequenced together and (2) that products should be sequenced in increasing thickness for high-density products due to constraints in the curing oven.

In the refined version of Study C, the variable for producing out of the preferred sequence was found to be statistically significant for all three PFs analysed, with each violation of preferred planning rules resulting in 500 – 970 kg per hour in lost productivity on average for one hour runs, equating to 5-9% of the line’s capacity. The effect of suboptimal sequencing is even more detrimental for shorter runs.

Study D applies a similar logic to Study C when modelling the effect of sequencing products on the line by using the rules agreed upon by production planners. While the results of Study D are not published in detail in the full-text article, the results from the Lasso regression show that scheduling products out of the preferred sequence is detrimental to performance and statistically meaningful in seven of nine product groups. The coefficients for the sequencing variables were also the largest coefficients in absolute magnitude of all variables assessed for five of nine product groups, with planning out of the preferred sequencing resulting in 320-960 kg per hour in lost process productivity, equating to 4-12% of the line’s capacity. These results are in alignment with the results from Study C regarding the direction and magnitude of the correlation between sequencing and process productivity.

Study E adds a new perspective for the insulation company regarding what may constitute the preferred sequence by examining the percent change in the maximum process productivity, referred to as the maximum observed, sustainable, feasible throughput (MOSFT) target, across subsequent products. The results from the analyses of two insulation production lines show
that if the MOSFT target of the previous run is lower than that of the current run, there will be higher lost process productivity on the current run because the process takes time to adjust to the higher output rate; however, if the MOSFT target of the subsequent run is higher than that of the current run, then the current run will experience less speed loss as the operators attempt to pre-emptively increase the output rate of the machinery in anticipation of the higher throughput target. The coefficients for these two sequencing variables are more difficult to interpret in operational terms, but the results show that a 10% difference in MOSFT targets between two consecutive runs can result in a 1.0-1.8% loss or gain in process productivity based on the identified relationships.

Increasing run length and optimising production sequencing at the insulation company can result in considerable additional gross profit if the company is constrained on capacity and the additional product could be sold; however, operations managers must consider other factors before adjusting production planning and scheduling methods. These factors include the availability of warehouse space, promised customer lead time, desired service level, minimum order quantities and the make-to-order (MTO)/make-to-stock (MTS) strategy.

5.2 Impact of Product Features and Process Bottlenecks

Study D, entitled ‘Which variety is free?’ aimed to identify product features of the insulation products that imposed additional operational costs by limiting process productivity. The product architecture of insulation materials is not complex regarding the number of components, but the process parameters required to achieve the desired properties in the finished material can be complex to control. Product features that were analysed in Study D include the density, height, length, width, lambda, binder content, application of fleece or foil on one or both sides of the product, dual density of the product and the stitching of wire into the insulation material. Some of these product features and the locations of where they are created on the production line are shown in Figure 5-6.

The magnitude of the impact of individual product features on process productivity identified in Study D cannot be explicitly stated due to confidentiality. Instead, some high-level findings are summarised as follows:

- Product dimension variables (i.e. length, width, thickness) are statistically meaningful in five of nine product groups with relatively small coefficients. Products with small thickness were most often related to lower process productivity because small thicknesses constrain the output of the curing oven, thus reducing the overall line throughput.

- Density-related variables are statistically meaningful in two of nine product groups and had moderately sized coefficients in both models. The density, together with the dimen-
sions of a product and the line speed, directly impact the overall throughput of the insulation line. All other factors being equal, it is logical that products with a lower density would be related to reduced process productivity.

- The percentage of binder used was statistically meaningful for one of nine product groups, though the coefficient for the binder was small.

- One product feature found to be ‘free’ for all product groups is the application of fleece to one side of the insulation. When fleece is applied to one side of the insulation material, the product is less likely to fail visual inspections for aesthetic nonconformities because minor deformities in the insulation are covered by the fleece, thus leading to an increase in process productivity compared to products without fleece.

*Figure 5-6 Insulation product features and their production processes, from (Moseley, Myrodia, et al., 2017)*

Studies C and E do not directly include product features in their models, but they do include other product-related variables, such as the amount of recycled waste material included in the batch (*RECYC* in Study E), notable quality issues for individual products (*QUAL* in Study D) and the PF (Study C). The amount of recycled waste material inserted into the product is significantly related to process productivity in Study E, most likely because it serves as one of the primary sources of raw material for upstream processes. If recycled material is not available for a product that can receive it, the process productivity decreases with respect to the historical maximum process productivity for the product (i.e. speed loss). The fact that a lack of recycled waste material reduces process productivity is an interesting conundrum faced by the insulation lines studied, namely because it is in the interest of operations managers to reduce the downstream waste that is recycled in the first place. The diagram of the insulation process in Figure 5-1 shows the recycled waste loop that capitalises on the circularity of the insulation materials while simultaneously imposing additional costs for processing the waste material. Operations managers at the insulation company are aware that they should minimise the waste material,
which is granulated and dosed back into the process, to optimise the net throughput of their lines and to avoid reprocessing the same material a second time.

Within the broad product range at the company, quality specifications vary across products, with the most stringent specifications belonging to the products that are most visible to end users once installed. Quality issues in the insulation process are typically not detectable until the product passes through the curing and cutting processes. At this stage, downstream operators will inform upstream operators if there is an issue and will request that the primary speed be reduced so that they can troubleshoot the issue. In Study E, quality issues occurred in 11-14% of the batches analysed and are linked to a loss of 0.5% of ideal process productivity on both production lines.

PV was also found to influence process productivity by creating different bottlenecks on the production line. The creation of bottlenecks on the line with different product variants stems from the integrated, highly automated nature of the production lines at the insulation company, which requires upstream processes to be slowed down if a downstream process needs to slow down to achieve a certain product property or feature. Study D investigated these product differences in production, and the results show that products could be grouped for analysis based on their shared bottleneck machine on the production line. An analysis of the productivity reveals significant differences across bottleneck groups, thus motivating the separate assessment of each bottleneck group in isolation (Moseley, Myrodia, et al., 2017). Study E also addresses the issue of production bottlenecks by assessing the lost process productivity for each product in relation to its own historical maximum process productivity. Quantifying process productivity in this way normalises the data across products, allowing all products to be assessed together. The approach in Study D allows for an in-depth view into the nature of the PV→OP performance in a process industry company, highlighting specific causes of lost process time productivity related to product architecture.
6 WHAT METHODS CAN BE USED TO BETTER MANAGE PRODUCT VARIETY AND ITS EFFECTS IN PROCESS INDUSTRIES?

‘Identify levers and implement with rigor’. – CEO of the insulation company

The final group of findings is related to a set of methods, or levers, for managing PV and its effects. The methods presented include a product portfolio optimisation model, a framework for assessing speed loss in process manufacturers and product wheels for improving production scheduling. From the many possible PV management methods that could have been explored, the methods presented are selected based on the literature, the findings from Section 5 and the potential for making a theoretical contribution. OM literature describes both the marketing and operational aspects of PV management (Berry and Cooper, 1999; Götzfried, 2013; Silveira, 1998), with marketing literature primarily concerned with optimising the product assortment to maximise the sales, profit and market share of a firm, while OM literature is primarily concerned with improving the OP of the value chain. For this reason, methods addressing both marketing and operational aspects are explored in this section, though the operational perspective is dominant due to the scope of the thesis.

The methods presented in Studies F, G and H (see Table 6-1 for summary) directly impact the product management, production and production scheduling functions within a firm. In the full-text versions of the three studies (see Appendix), each method is detailed, tested in a case company and evaluated through the lens of their respective academic domains.

Table 6-1 Overview of the methods tested for product variety management

<table>
<thead>
<tr>
<th>Method</th>
<th>Objective</th>
<th>Domain</th>
<th>Primary benefit</th>
<th>Case data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study F</td>
<td>Product portfolio optimisation based on substitution and linked revenue</td>
<td>Manage product variety for increased contribution margin using optimisation and product substitution considering linked revenue between products</td>
<td>Product management</td>
<td>One market within a global producers of insulation materials in Western Europe</td>
</tr>
<tr>
<td>Study G</td>
<td>Framework for assessing speed loss causes in the process industries</td>
<td>Assess the magnitude of the effect of PV and other factors on speed loss using a tested framework</td>
<td>Production</td>
<td>One insulation factory in Western Europe</td>
</tr>
<tr>
<td>Study H</td>
<td>Product wheels for production scheduling</td>
<td>Demonstrate the benefits and limitations of product wheels for scheduling in the process industry</td>
<td>Production Planning</td>
<td>One baked goods manufacturer in Northern Europe</td>
</tr>
</tbody>
</table>
Knowledge related to which methods are proven to improve the management PV and its effects can aid operations managers in implementing the most appropriate PV management initiatives based on their business needs. This research augments the existing PV management frameworks in the literature by specifying which adaptive and flexibility strategies could be more applicable to process industry firms (Silveira, 1998).

6.1 PRODUCT PORTFOLIO OPTIMISATION BASED ON SUBSTITUTION

The first method presented here focuses on the commercial viewpoint of PV and how to make decisions on the product portfolio that both satisfy customer demand and improve financial performance. The following summary of Study H presents an optimisation model that maximises the total contribution margin (CM) (i.e. gross profit) earned by the firm by making product portfolio decisions while considering product substitutability and linked revenue.

Substitutability is a concept that is discussed in the literature from a commercial standpoint as a method to logically rationalise the product portfolio while maintaining adequate coverage of market needs (Dixit and Stiglitz, 1977). It is also described as the behaviour customers exhibit when they purchase a less desirable product because their desired product is out of stock (Kök and Fisher, 2007). Substitution can be both vertical (i.e. the substitution of products that differ in quality, price or value) and horizontal (i.e. substitution of products with similar quality, price or value) (Ye, 2014). While many factors can influence PV decisions (Brownstone, 1999; Huang et al., 2011; Inderfurth, 2004), profitability is often used to determine which products to keep and which products to eliminate (e.g. products with higher profitability are kept in the assortment, while products with lower profitability are eliminated) (Kök and Fisher, 2007). Mathematical models and dynamic programming (Yaman, 2009; Zhou and Sun, 2013) have been used to model product substitution before, but the use of OR models to simulate product substitution is limited.

The model is formulated as a mixed integer programme (MIP) and can be viewed in the Appendix. The model objective function maximises the CM per product under adjusted sales volumes and then subtracts the complexity costs (CC) of maintaining a SKU in the assortment. The CC is assumed equal across all SKU types to reflect overhead expenses due to master data, sales handling and other costs not included in the CM calculation (Hansen et al., 2012). Various constraints are created for ensuring the following: (1) that SKUs without sales are removed from the assortment, (2) SKUs kept in the portfolio sell a minimum of 50% of the sales volume from the previous year, (3) sales are lost if a SKU possesses related sales with SKUs that are closed, (4) sales are gained if a closed product is substitutable with a kept SKU (5) and a minimum number of SKUs containing a feature required by the customer are kept. A substitution parameter has been developed based on three elements: the degree of similarity between four key product features for each pair of SKUs, the percentage match required between two SKUs
before qualifying as substitutable and the maximum amount of revenue from a closed SKU that can be transferred to a substitutable SKU.

Once developed, the model was tested using data from an insulation manufacturer operating in Western Europe. A total of 699 SKUs belonging to 23 product families are included in the model. Three scenarios are created by adjusting the levels of four parameters in the model: the degree of match required between two SKUs before qualifying for substitution, the maximum revenue that can be transferred from a closed SKU to a kept SKU, the related sales loss and the fixed CC level. An overview of the precise levels for each parameter in the three scenarios is shown in Table 6-2. The scenarios are designed to increase the flexibility in the substitution parameters as the model optimism increases. Each model scenario was solved to optimality using the General Algebraic Modelling System (GAMS) optimisation software.

The results of the optimisation were assessed in relation to the current situation and to a manual substitution method performed by production managers at the company. For each scenario, the number of SKUs kept, net sales, CM, CC and adjusted CM (i.e. total CM minus total CC) are calculated to estimate the financial impact of the portfolio decisions. The adjusted CM is calculated as an estimate of the profit generated by the portfolio after accounting for PV-driven fixed costs.

Table 6-2 Input parameters by scenario, from Myrodia et al. (2017)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Degree of match required for substitution</th>
<th>Max % revenue substituted</th>
<th>% Sales which can be lost if related products are closed</th>
<th>Fixed complexity cost (EUR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>100%</td>
<td>50%</td>
<td>100%</td>
<td>7,000</td>
</tr>
<tr>
<td>Pragmatic</td>
<td>98%</td>
<td>66%</td>
<td>50%</td>
<td>8,500</td>
</tr>
<tr>
<td>Optimistic</td>
<td>95%</td>
<td>75%</td>
<td>25%</td>
<td>10,000</td>
</tr>
</tbody>
</table>

Figure 6-1 Results of optimisation model compared to current situation and manual substitution
A summary of the results is shown in Figure 6-1, where it can be seen that the MIP model eliminates the most SKUs and simultaneously provides the highest adjusted CM in all three scenarios. It can also be seen that as the scenarios range from conservative to optimistic, the total adjusted CM decreases across the three MIP models due to the rising fixed CC per SKU. The MIP model proposes to remove between 36-40% of the SKUs from the portfolio, while only 35-36% of the SKUs were removed in the manual substitution across the scenarios. While these ranges may appear close, the gap between the adjusted CM for the manual substitution versus the MIP model widens as the scenarios become more optimistic. This could be attributed to the increasing opportunities for substitution that are available in the pragmatic and optimistic scenarios, which are not easily identified by the human mind. Overall, the MIP model improves the CM by 1-3%, and the complexity adjusted CM from 15-32% when compared to the current situation, depending on the scenario employed by the company. Moreover, it does so in seconds compared to the 38 hours required in the manual substitution scenario.

6.2 Analysis of Production Speed Loss

Key to managing the negative PV→OP relationship is understanding the relationship’s magnitude in each production context. To assist operations managers in this task, a framework for identifying causes of lost production throughput, here referred to as speed loss, and quantifying their relative effects is developed and presented. Some methods discussed in the total productive maintenance literature (TPM) have been shown to help reduce speed loss, including basic target setting, root cause analysis and incremental process improvements (Benjamin et al., 2015; Nakajima, 1988, 1989); however, these methods fail to address the complexity of discerning the relative impact of individual variables on speed loss in process manufacturing settings. Process manufacturers are characterised as having a high degree of interdependence between process variables (Orfi et al., 2011). Such characterisation renders methods such as the Pareto analysis, which is frequently used in discrete manufacturing industries to prioritise improvement opportunities, less appropriate for continuous improvement in process industries.

Using a combination of literature from the fields of TPM, change management and OM, a seven-step framework has been developed to guide academics and practitioners in the systematic assessment of speed loss causes on process manufacturing lines. The framework was tested at the insulation company using one of their production lines. The company operates using a continuous flow production process and has identified speed loss as a significant source of capacity loss, thus making the company a suitable case company for testing the framework.

The proposed framework, shown in Table 6-3, includes the necessary calculation of speed loss, as per Nakajima (1989), as well as a multiple regression analysis component, which has been shown to be an appropriate method for analysing process productivity in process industries (Anderson and Sedatole, 2013; Berry and Cooper, 1999). The framework is structured so that the human resource foundation for speed loss analysis is set at the very beginning, following the best practice for Lean manufacturing and change management projects (Costa et al., 2018;
Kotter, 2012). Steps 2-7 follow a logical flow of dependence with emphasis on assessing data readiness and determining target production speeds because these two areas are often neglected by companies (Ahmed et al., 2004; Hedman et al., 2016; Ljungberg, 1998). The final step allows manufacturers to use the analysis results to drive improvement activities following the logic of existing TPM and speed loss frameworks (Benjamin et al., 2015; Nakajima, 1989).

For each step of the framework, detailed descriptions and justifications for the step are included in the Appendix.

Table 6.3 Proposed framework for the assessment of speed loss causes in process manufacturers, adapted from Trattner, Hvam, Haug, et al. (2019)

<table>
<thead>
<tr>
<th>#</th>
<th>Step</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Secure human resource(s) to lead the speed programme</td>
<td>Identify an individual responsible for data collection, analysis and regular reporting to relevant stakeholders.</td>
<td>(Costa et al., 2018; Iyede et al., 2018; Kotter, 2012; Zargun and Al-Ashaab, 2013)</td>
</tr>
<tr>
<td>2</td>
<td>Ensure data readiness to begin a speed programme</td>
<td>Assess that the required data for calculating speed loss is available at the firm. If unavailable, then instate manual or automatic methods to collect the data.</td>
<td>(Ahmed et al., 2004; Berry and Cooper, 1999; Fisher and Ittner, 1999; Hedman et al., 2016; Ljungberg, 1998; Moseley et al., 2016; Noterdaeme et al., 2018)</td>
</tr>
<tr>
<td>3</td>
<td>Determine the target speed for each product</td>
<td>Identify the designed speed for equipment from the manufacturer or use maximum demonstrated, feasible, sustainable speed from historical data if designed speed is not available.</td>
<td>(Amaran and Bury, 2016; Fernandez and Sanchez, 2012; Hedman et al., 2016; Jonsson and Lesshammar, 1999; Litzen and Bravo, 1999; Ljungberg, 1998; Ogle and Carpenter, 2014)</td>
</tr>
<tr>
<td>4</td>
<td>Calculate the speed loss for the process</td>
<td>Apply the speed loss calculation $\text{Speed loss} = 1 - \frac{\text{Actual throughput}}{\text{Ideal throughput}}$. Speed loss can be calculated at the batch, product, day or minute level, with the calculation complexity varying with the level of product mix heterogeneity.</td>
<td>(Nakajima, 1988; Huang, 2003)</td>
</tr>
<tr>
<td>5</td>
<td>Formulate hypotheses for possible causes of speed loss and gather relevant data</td>
<td>Develop a set of expert hypotheses by interviewing process engineers, production supervisors, design engineers and operators to uncover which factors may be related to speed loss, ensuring that there is a logical causal link for each hypothesis. Gather relevant data.</td>
<td>(Creswell, 2014)</td>
</tr>
<tr>
<td>6</td>
<td>Quantify the impact of the speed loss causes</td>
<td>Apply appropriate regression analysis technique to the aggregated dataset to identify statistically significant factors.</td>
<td>(Anderson, 1995, 2001; Anderson and Sedatole, 2013; Berry and Cooper, 1999; Cochrane and Orcutt, 1949; Wooldridge, 2006)</td>
</tr>
<tr>
<td>7</td>
<td>Identify significant causes of speed loss and eliminate them</td>
<td>For each factor, use the statistical significance and coefficient magnitude and direction to create a prioritised list of actions to mitigate speed loss.</td>
<td>(Benjamin et al., 2015; Nakajima, 1989)</td>
</tr>
</tbody>
</table>
In step one, two researchers and a factory manager implemented each step of the framework at the insulation company with support from operations analysts at headquarters. This team was selected to reflect diverse perspectives on the production process at the insulation company and to aid in triangulation of the data. The researcher acknowledges that step 1 was only partially tested because the method within the framework was not implemented solely by resources at the insulation company.

Assessing production data for step two revealed that reliable speed data was available from sensors on the production line studied. The most appropriate speed measure for analysis was found to be gross throughput (i.e. a combination of newly spun fibres and recycled fibres) because it is directly controllable upstream in the process. Considering the flexibility of the process and the average run length for production batches, a time interval of 30 minutes was selected for gathering production data.

In steps three and four, an assessment of the target speeds per product revealed that factory targets were often exceeded by the production line (as seen in Figure 6-2), thus justifying the use of MOSFT targets for gross throughput (Ogle and Carpenter, 2014). The time-weighted average speed loss was then calculated using three months of production data together with the MOSFT targets, resulting in a 6% speed loss for the production line analysed.

![Figure 6-2 Gross throughput rates compared to factory targets and maximum observed, sustainable, feasible targets (MOSFT) (y-axis labels removed for confidentiality), from Trattner, Hvam, Haug, et al. (2019)](image)

Next, hypotheses related to the potential causes of speed loss were gathered from interviews with the factory manager and operations analysts as well as from operator production logs that
documented perceived causes of speed loss per production batch. The combined set of hypotheses was consolidated and reviewed by the researchers together with the factory manager for potential causality based on mechanical workings of the line. Fifteen hypothesised speed loss causes, which were deemed potentially causal and for which data was available, were included in the final data set.

In step six, a regression analysis was performed on the final data set, and maximum likelihood estimates were calculated. Of the fifteen variables tested, twelve showed statistically significant relationships with speed loss on the line studied. Variables that were expected to have the highest impact on speed loss did not have the highest coefficients in the model when evaluated along with the other variables. The results were reviewed along with operations specialists, who were surprised by the findings because they hypothesised that factors such as by-product drain would account for greater speed loss but ultimately agreed to the conclusions after the discussion.

Last, the significant variables were listed in order of importance in relation to speed loss and given to the factory manager and operations specialists at the insulation company to prioritise speed loss reduction initiatives.

6.3 PRODUCT WHEELS FOR PRODUCTION SCHEDULING

The primary aims of Study H were to present an overview of the state of production scheduling practices in the baking industry and to test the product wheel methodology for applicability in the baking context; however, the study further reveals that production planning and scheduling methods should be adapted to the unique PV situation at a company operating within the process industry.

Production planning serves a critical link between market demand and production output. Planning is a particular challenge in the baking industry due to the increasing PV, time-sensitive fermentation process, handling of allergens, sequence-dependent changeovers and limited product shelf-life (Akkerman and van Donk, 2009; Higgins, 2013). An example of the challenges of production planning in the baking industry is provided by a Danish producer of frozen baked goods catering to the convenience food market, here called Baking Company. Baking Company faces many of the challenges that exist in the larger context of baked goods manufacturers, including increasing PV and PC. For these reasons, Baking Company was selected to test the applicability of the product wheel using case research.

The production process at Baking Company is characteristic of the process industry as it involves batch, continuous and discrete operations (Abdulmalek et al., 2006). The process (see Figure 6-3) begins as a batch process, where dough is mixed in large quantities based on a recipe. The dough is then transferred to a lamination machine, which layers and extrudes the dough continuously until a discretisation point at the make-up station where individual products are cut, formed and seasoned. Next, the products proceed into a proofing oven where the
dough can rise before being either frozen or partially-baked, cooled and frozen. Last, the products are packaged and stored in cold storage. Six major product segments form the product assortment at Baking Company, including Danish pastries, sausage rolls, pastry bars, focaccia bread, buttermilk horns and pastry rolls.

![Production process at Baking Company](image)

*Figure 6-3 Production process at Baking Company, from Trattner, Herbert-Hansen, et al. (2018)*

The method tested for applicability to the process industry is called the product wheel, which is a heuristic method for creating cyclic production schedules using economic lot sizing and product clustering (King, 2009). King (2009) proposes the following ten steps for creating a product wheel:

1. Decide which assets would benefit from product wheels.
2. Analyse product demand variability.
3. Determine the optimum production sequence.
4. Calculate the shortest wheel time based on time available for changeovers.
5. Estimate the economic optimum wheel time based on the Economic Lot Size (ELS) model.
6. Determine the basic wheel time and determine which products are made on each cycle and the frequency for other products.
7. Calculate inventory levels to support the wheel.
8. Repeat steps 3-7 to finetune the design.
9. Revise all scheduling processes, as appropriate.
10. Create a visual display to manage the levelled production.

Steps 1-7 were tested at Baking Company to assess its appropriateness in the baked goods manufacturing context and hence in the process industry. Steps 8-10 could not be implemented due to constraints at the factory. One year of data from the enterprise resource planning system (ERP) and manufacturing execution system (MES) for a single high-volume production line at Baking Company were analysed and used to develop product wheels. Additional data were collected through site visits, product documentation sheets, sales records and interviews with production planners, operators and factory managers onsite.

To perform step 2, sales data from the full year of 2014 were collected and assessed using the coefficient of variation in sales. Graphing the variation in demand against the average demand and dividing the products into quadrants, as seen in Figure 6-4, allows for determining which products should use a MTO scheduling policy and which products should follow a MTS scheduling policy. Based on this analysis and the decision to classify Q1 and Q3 products as MTS
products, a total of 81 of the 86 products were selected as MTS products because they had a high average demand and a low demand variation.

![Figure 6-4 MTO-MTS analysis using variation in monthly demand (logarithmic scale), from Trattner, Herbert-Hansen, et al. (2018)](image)

Continuing with steps 3 through 7 of the product wheel framework, the optimum production sequence, ELSs and necessary inventory levels were determined to support the product wheel (see full-text in Appendix – Study G). The ELS exercise revealed that most products have economic cycle lengths that are greater than eight weeks (see Figure 6-5). Eight weeks was deemed too long to warrant inclusion in a cyclic production schedule because producing a product once every three or more months is unlikely to build economies of repetition. Excluding products with a cycle length of over eight weeks resulted in only 35 products being included in the product wheel. Two product wheels were then developed by combing the ELS and the product sequence, which minimises changeover time. An example of one of the product wheels for the first four weeks of an eight-week production cycle is shown in Figure 6-6. The product wheel contains green, high-volume products, yellow, medium-volume products and grey placeholder time allotments, which can be used to make products with a lower order frequency.

The costs of changeover and inventory were calculated and compared for the production scheduling utilised in 2014 and the revised production schedule shown in the product wheel (see Table 6-4). By adopting the product wheels designed in this study, Baking Company can save upwards of EUR 100,000. The product wheels were also found to be robust in preventing stock outs after increasing the lot sizes for two products, Scones G and Sandwich bread R.

Product wheels were shown to be beneficial to the financial and operational performance at Baking Company; however, the product wheel approach was difficult to implement for the line studied due to the high PV assigned to the line and the sequence-dependent changeover times.
the variety induces. It is expected that an OR model would be able to improve the performance of the production schedule in high-variety baking industry contexts.

**Figure 6-5 Economic cycle lengths for MTS products, from Trattner, Herbert-Hansen, et al. (2018)**

**Figure 6-6 Product wheel for weeks 1-4, adapted from Trattner, Herbert-Hansen, et al. (2018)**

**Table 6-4 Product wheel impact on setup and inventory costs for 35 MTS products, from Trattner, Herbert-Hansen, et al. (2018)**

<table>
<thead>
<tr>
<th></th>
<th>Changeover Cost (EUR)</th>
<th>Inventory Holding Cost* (EUR)</th>
<th>Total (EUR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Schedule (2014)</td>
<td>226,400</td>
<td>217,100</td>
<td>443,500</td>
</tr>
<tr>
<td>Product Wheel</td>
<td>180,200</td>
<td>149,000</td>
<td>339,900</td>
</tr>
<tr>
<td>Savings</td>
<td>46,200</td>
<td>57,400</td>
<td>103,600</td>
</tr>
</tbody>
</table>

* Inventory cost includes the cost of safety stock.
Note: costs and savings calculated only for the 35 products assessed in the product wheel.
7 INSIGHTS INTO REDUCING AND MANAGING PRODUCT VARIETY FROM THE INSULATION COMPANY

‘Continuous improvement is better than delayed perfection’. - Mark Twain

The previous sections revealed significant potential benefits regarding effective PV management, particularly through the optimisation of the product assortment, reduction of speed loss and improvement of production planning practices. To convey the industrial relevance of the research findings and to provide a collection of facts that can inspire future research questions, this section presents longitudinal, anecdotal evidence of a real company attempting to improve its PV management in the process industry. Each aspect of the study was carried out at the insulation company over the course of three and half years. During this period, the insulation company pursued programmes for PV reduction (i.e. SKU rationalisation), speed loss improvement and production scheduling optimisation and achieved operational and financial benefits from the efforts across multiple factories and sales units. Due to confidentiality agreements, some details from the case are omitted.

7.1 SKU RATIONALISATION PROGRAMME

Led by the CEO, top management at the company set the reduction of product portfolio complexity as a top priority in 2015 and initiated a global programme to develop methods to address increasing PV. It was at this point that the researcher was contacted to support the analysis of product profitability and to develop key performance indicators (KPIs) for tracking the reduction of PV.

At the onset of the project, it was clear that the insulation products were proliferating as new variants were added to existing product lines upon customer request. The sales department was observed to dominate PV decisions without a transparent view of SKU profitability and with no process for removing SKUs from the assortment. Within production, the negative effects of additional PV were evident through a high number of product changeovers on certain production lines, some of which were constrained on capacity. From an organisational perspective, the distributed decision making in product management across the business units (BUs) in the company led to a lack of clarity in product strategy within the company. Each of these factors played a role in placing SKU rationalisation on the agenda of top management.

The insulation manufacturer consists of 18 individual BUs operating in different markets, with each BU managing its own assortment. Most of the BUs represent collections of factories and markets around the world, while some BUs operate primarily as sales organisations for niche insulation products. Fifteen of the BUs participated in the SKU rationalisation exercise at the request of top management at the insulation company. Using analyses and methods developed
at headquarters, each BU individually assessed its product portfolios for improvement opportunities. The mandate for change originated from the CEO and was sent through the management hierarchy to each BU, while analysts at headquarters supported the BUs upon request.

From the perspective of headquarters, the SKU rationalisation programme consisted of three phases: methodology development, global implementation and training and SKU rationalisation. Activities for each of these phases took place from August 2015 to December 2018 (see Table 7-1 for details of each phase).

Table 7-1 Phases of SKU rationalisation at an insulation manufacturer

<table>
<thead>
<tr>
<th>Phase</th>
<th>Dates</th>
<th>Activities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Methodology development</td>
<td>08/2015 – 12/2016</td>
<td>Created standardised method to assess products based on contribution margin (CM) and net sales per SKU per market. Determined a threshold of 2000 EUR CM per SKU to segment ‘unprofitable’ and ‘profitable’ SKUs. Developed KPIs to track SKU count and performance.</td>
</tr>
<tr>
<td>Global implementation and training</td>
<td>01/2016 – 12/2016</td>
<td>Issued monthly SKU reports to management. Trainings in SKU analysis and reporting methods given to designated SKU managers in each business unit. Changes to portfolios driven through the management hierarchy based on their own ambition level. Some BUs initiate changes to portfolios.</td>
</tr>
<tr>
<td>SKU rationalisation</td>
<td>01/2017 – 12/2018</td>
<td>Changes made to portfolios across the 18 BUs. Targets on SKU KPIs were set per market and followed up using quarterly SKU reports to management.</td>
</tr>
</tbody>
</table>

The researcher collaborated with the supply chain team in headquarters between two and four days per week during the entire project period. The main tasks of the researcher were assisting with KPI development for the SKU programme, SKU rationalisation methodology, quantification of the impact of SKU rationalisation and reporting of the SKU KPIs to management over the three-year period. During this time, the researcher had full access to sales, profit and production data at the company and participated in a minimum of one meeting per year with the SKU manager of each BU regarding their SKU rationalisation efforts. The data presented were gathered through these sources.

7.2 SKU RATIONALISATION APPROACH

The SKU rationalisation efforts were framed and communicated by management as a means of creating additional throughput on the production lines at the insulation company. As low-volume SKUs were believed to consume disproportionally more production and supply chain capacity through increased changeovers and transactions, low-volume SKUs were targeted for rationalisation so that higher volume, more profitable SKUs could be sold in their place. The approach was of relevance for the BUs that were running at or over their production capacity. Reductions in operational costs resulting from SKU rationalisation were sought by some BUs, but this was not the primary objective of the project. The SKU rationalisation approach at the
The insulation company consisted of three main tools: a product A-B-C classification method, cross-functional product portfolio review and quarterly reporting and follow-up. Each method is described in the subsequent paragraphs.

The product A-B-C classification method used by the insulation company, which is shown in Figure 7-1, is based on the Pareto analysis of net sales and CM data, as has been utilised in the literature (Hansen et al., 2012; Hvam et al., 2019; Wilson and Perumal, 2009). The purpose of the analysis is to segment SKUs into clusters that represent profitable products and unprofitable products. During the project period, A-B-C analyses were performed quarterly using one year of historical data for each SKU in each market. Values for net sales and CM were taken from the profit data within the centralised ERP system at the company. For each of the six boxes in the A-B-C model, different strategies were recommended by the supply chain team at headquarters. A diagram depicting the strategies suggested for each area of the A-B-C model along with example data per SKU is provided in Figure 7-2. The diagonal line in the upper-right corner of the figure represents the average CM percentage for the SKUs shown.

The threshold for determining profitable and unprofitable products was set to 2000 EUR in CM per year. This was determined using an activity-based costing approach in which the costs for master data management, sales order handling, warehouse space and factory overhead were quantified for low-volume products, with the sum equating to approximately 1200 EUR. As this cost did not include marketing or administration expenses or a profit margin, the 2000 EUR threshold was agreed upon by the supply chain department and the CEO as a reasonable starting point for rationalising unprofitable SKUs. The net sales thresholds were established using the Pareto principle, representing the top 80% of net sales, the middle 15% of net sales and the bottom 5% of net sales (Hvam et al., 2019; Koch, 2008).

![Figure 7-1 Product A-B-C analysis model for SKUs](image-url)
The second aspect of the SKU rationalisation approach involved key stakeholders across the departments of each BU in discussions regarding which SKUs should be kept and which should be eliminated. The SKU rationalisation process was first driven by the supply chain function of each BU, with a designated SKU manager coordinating activities and local reporting. This was done because the supply chain departments understood the impact of PV on the value chain and possessed analytic capabilities; however, some BUs appointed individuals in finance or product management as SKU managers based on the competence of the person and the level of the organisation at which product portfolio decisions are made.

One of the primary tasks of the SKU manager was to coordinate regular cross-functional reviews of the product portfolio. A swim lane diagram depicting the best practice business process at the insulation company for the cross-functional review is shown in Figure 7-3, which was developed by the supply chain team. It was estimated that an in-depth portfolio analysis would require approximately eight weeks if the necessary resources are appropriately allocated to their tasks. The analysis and review phases are driven by product management in the example provided, with representatives from sales, supply chain, production and master data involved in the assortment design tasks. Dedicating a cross-functional team to assortment design ensures that all business perspectives of the portfolio can be expressed and incorporated into the new assortment design. In addition, the cross-functional nature of the team also allowed for SKUs with low revenue and profitability to be addressed through multiple methods, including closing the SKUs and transitioning customers to a substitutable SKU, increasing the prices of the SKUs, adjusting promised lead times for the SKUs, setting minimum order quantities for the SKUs or placing a service charge for low volume orders. Before making major changes to the assortment, all BUs require a sign-off from their respective Managing Directors. After the sign-off, tasks such as informing customers of the coming portfolio change, updating pricelists, depleting stock and closing the products in the ERP system can be performed by the relevant functions.

Figure 7-2 Product A-B-C analysis model with suggested strategies and example data per SKU
**Figure 7-3** SKU rationalization process showing tasks for each department

<table>
<thead>
<tr>
<th>Ongoing</th>
<th>Week 2-8</th>
<th>Week 3-4</th>
<th>Week 1-2</th>
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</tbody>
</table>

- **Sales**
  - Prepare knowledge of current portfolio logic and price positioning
  - Contribute to competitor analysis and identify market trends

- **Supply Chain**
  - Perform initial ABC analysis and suggest initial targets
  - Set targets for portfolio size, profitability and production efficiency

- **Product Management**
  - Define assortment strategy
  - Perform competitor analysis and identify market trends

- **Master Data**
  - Prepare proposal for standard dimension, packaging, etc.
  - Review SKUs for removal, price up, and substitution (e.g. packaging, thickness, etc.) and set delivery conditions

- **Production**
  - Define new assortment, determine the price increases and create action list
  - Quantify impact of new assortment (effect of price up)
  - Prepare proposal for new assortment

- **Warehouse**
  - Publish and distribute new product assortment
  - Update price lists
  - Communicate price changes, new assortment and delivery conditions

- **Headquarters**
  - Capture supply chain impact
  - Update planning rules and delivery conditions

- **Ongoing**
  - Remove SKUs from warehouse
  - Capture production impact
  - Create new SKUs, close old SKUs

- **Assist with effects quantification (as needed)**

- **Track complexity reduction through SKU KPIs (**Quarterly**)**

- **Report on SKU KPIs to Management (**Quarterly**)**

- **Approve additional SKUs to product assortment**

- **Approve new assortment**

- **Ongoing**
The alignment of business processes was not possible across BUs due to organisational and cultural differences. This finding presents an open research issue regarding how to approach PV rationalisation projects in different culture contexts within the same organisation. Most BUs carried out the cross-functional SKU review once per year for each product segment before the yearly price adjustment and the printing of the new pricelists.

For the third element of the SKU rationalisation approach, the researchers and the analysts at headquarters developed a set of KPIs to track SKU rationalisation efforts and portfolio profitability. Standard reports were created in the business intelligence system to measure the following for each BU and for the entire company:

- **Active SKUs**: SKUs that are flagged in the ERP master data as available to be produced and sold in the BUs on the day of reporting;

- **Sold SKUs**: SKUs sold from a BU in the previous 12 months, excluding any SKUs that may have been closed for sales or production during that time;

- **Unprofitable SKUs**: SKUs sold from a BU in the previous 12 months and earning less than 2000 EUR in CM during that period, excluding any SKUs that may have been closed for sales or production during that time; and

- **CM per SKU**: A measure of the total CM in Euros earned by the company in the previous 12 months divided by the total SKUs sold by the company during the same period.

The measures listed were reported monthly or quarterly to top management and the SKU managers of the BUs. An excerpt from this report is shown in Figure 7-4, which shows the overall portfolio changes summed for all BUs from the full year of 2015 to full year of 2018. In the figure, the KPIs for Active SKUs, Sold SKUs and Unprofitable SKUs are nested in a stacked bar chart revealing the number of Unsold SKUs (Active minus Sold SKUs), the number of Sold SKUs earning above 2000 EUR in CM per annum (Sold SKUs minus Unprofitable SKUs) and the number of Unprofitable SKUs. Over 40,000 Active SKUs equating to roughly half of the total assortment were closed for sales and production during the three-year period, with most SKU closures involving SKUs that had no sales in the previous year; however, Figure 7-4 shows that the BUs have closed approximately 20% of their Sold SKUs and have made a 33% reduction in Unprofitable SKUs since 2015.

The Euros of CM per SKU increased by 50% from 2015 to 2018, reflecting the profit increase per product resulting from the SKU rationalisation initiatives, price increases and sales growth at the insulation company.
7.3 The Effects of SKU Rationalisation

The financial effect of SKU rationalisation was quantified quarterly in 2017 and 2018 by performing an analysis of the ratio of Unprofitable SKUs to Sold SKUs earning above 2000 EUR in CM per year. The analysis quantifies the CM increase achieved by decreasing the ratio of Unprofitable SKUs in the assortment compared to the previous year. An example for such a calculation is shown in Table 7-2, where mock CM data are used to preserve confidentiality for the company. The SKU mix impact calculation compares the percentage increase (or decrease) in Unprofitable SKUs and Sold SKUs with a CM greater than 2000 EUR per year multiplied by the CM per SKU from the previous year for each group and then scales the figures by the total Sold SKUs from the current period. The total CM impact from 2017 compared to 2016 was over 10 million EUR, and the total CM impact from 2018 compared to 2017 was found to be nearly 40 million EUR. While this margin increase is difficult to trace directly within the EBIT at the firm, it presents a conservative estimate of the benefit of removing unprofitable products and selling products with higher profitability.

Further benefits of SKU rationalisation were observed in the supply chain and customer service. One BU experienced decreasing order entry errors and warehouse picking errors and improved order confirmation times after reducing its assortment from 1,332 SKUs to 501 SKUs in 2016. Feedback was also received by the BU from customers who expressed positive opinions of the greater clarity in product assortment.

One unexpected benefit of SKU rationalisation is that it prepared the organisation to transfer product data into a product information management (PIM) system. The PIM system, meant to
organise product data for presentation on e-commerce platforms, requires significantly less data than it would have otherwise due to the 51% reduction in Active SKUs.

Table 7-2 SKU mix impact calculation with mock CM data

<table>
<thead>
<tr>
<th></th>
<th># SKUs</th>
<th>% of Sold SKUs</th>
<th>CM (M€)</th>
<th>CM / SKU (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full year 2017</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold SKUs</td>
<td>25552</td>
<td>100%</td>
<td>40</td>
<td>1565</td>
</tr>
<tr>
<td>Sold SKUs &gt; 2k CM/yr</td>
<td>15201</td>
<td>59%</td>
<td>39</td>
<td>2566</td>
</tr>
<tr>
<td>Unprofitable SKUs</td>
<td>10351</td>
<td>41%</td>
<td>1</td>
<td>97</td>
</tr>
<tr>
<td><strong>Full year 2018</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sold SKUs</td>
<td>23420</td>
<td>100%</td>
<td>45</td>
<td>1921</td>
</tr>
<tr>
<td>Sold SKUs &gt; 2k CM/yr</td>
<td>14614</td>
<td>62%</td>
<td>44</td>
<td>3011</td>
</tr>
<tr>
<td>Unprofitable SKUs</td>
<td>8806</td>
<td>38%</td>
<td>1</td>
<td>114</td>
</tr>
<tr>
<td><strong>SKU Mix Impact</strong></td>
<td></td>
<td></td>
<td>1.68</td>
<td></td>
</tr>
</tbody>
</table>

* SKU Mix Impact = [(%UnprofSKU2018 - %UnprofSKU2017) × CM/UnprofSKU2017 + (%ProfSKU2018 - %ProfSKU2017) × CM/ProfSKU2017] × SoldSKU2017, where ProfSKU represents Sold SKUs > 2k CM/yr

7.4 OBSERVATIONS OF SKU RATIONALISATION

Being present at the insulation company over the three-year project allowed the researcher to observe the organisational benefits and challenges of implementing a PV reduction programme within an international manufacturing organisation.

The company-wide approach allowed for a clear set of standards and expectations to be communicated by top management; however, not all standards were entirely applicable for each BU. For example, SKUs for one product segment at the insulation company are sold primarily to building project contractors. To win a project bid, the insulation company must be able to produce all requested SKUs, including the low-volume SKUs with low profitability. This is a scenario in which the potential revenue of high-volume SKUs is linked to the availability of the low-volume SKU. To overcome this challenge for this product segment, the affected BUs have developed methods to assess the total profitability per project rather than to assess profitability at the SKU level.

When first introduced in 2015, the 2000 EUR CM threshold for unprofitable products was heavily critiqued by top managers as being too high for special products that are produced to satisfy large customers. Despite this, the CEO felt the threshold was too low and therefore upheld the initial 2000 EUR threshold. Throughout the project, the team that developed the 2000 EUR threshold communicated that it primarily applied to products that are produced and packaged on the main production lines without further manual assembly. PV affecting the main production lines was prioritised for reduction because PV is a known cause of production losses on the main lines and the main production lines account for a large portion of the overall operation costs at the company. Over the course of the project period, the researcher found that it was necessary to adjust the SKU KPIs to provide visibility of the PV affecting the main line.
Through the annual meetings with the individual BUs, it became evident that not every BU had implemented a cross-functional portfolio review to drive assortment changes. The BUs that did not use such a review were not as successful in rationalising the Sold SKUs, focusing on the simpler task of closing Unsold SKUs. It is easier for the BUs to close Unsold SKUs because these SKUs do not immediately impact the customer base, but there is little operational benefit to be gained because these SKUs have not been produced in over one year.

The extent of product rationalisation possible at the insulation company was found to depend on the product strategy at the firm and the market situation. The product strategy at the insulation company was to provide a full portfolio of building insulation products to service the general building insulation and speciality insulation markets. Due to this strategy, rationalisation efforts were limited because the BUs needed to ensure that at least one product line meeting each business application was kept in the assortment. The market situation was an important factor because BUs with capacity constraints had a hotter burning platform to improve the portfolio to release capacity for more profitable products.

The change management process in such a complex organisation with distributed decision-making power cannot be underestimated. The first 1.5 years of the project were primarily dedicated to developing the KPIs and methods for managing SKUs, communicating the methods to top management and training each of the fifteen BUs in the methods. While some progress in closing SKUs was made, it was a tumultuous year that resulted in many questions and critiques from the BUs, which resulted in slight adaptations to the methods and KPIs where management deemed appropriate. By the start of 2017, very little communication and training was needed because the expectation of SKU reductions was well-understood by management and the BUs. Currently in early 2019, the SKU rationalisation approach has been established in most BUs as a standard business process, with many BUs maintaining their reductions by using a ‘one-in-one-out’ policy for new production launches, a strategy commonly used in retail companies (Quelch and Kenny, 1995). This testifies to the commitment to the project from top management at the insulation company and the continuous communication of SKU rationalisation as a strategic priority.

The case of the insulation company also revealed the importance of clearly communicating the expected business benefits of SKU rationalisation and linking the project to both business and operations strategies. The intention of the SKU rationalisation project at the insulation company was always more focused on increasing throughput than reducing costs; however, this message did not permeate top management during the first two years of the project, and resistance to the project was evident. In 2018, the SKU rationalisation project was framed within a larger strategic initiative to increase throughput (measured in both kilograms and Euros) on the capacity-constrained production lines. This re-framing of the project led to a much greater buy-in from SKU managers and their teams in the BUs to address the Unprofitable SKUs, which consumed anywhere from 1-2% of the production capacity and brought very little monetary value to the business. It was also clear that increasing throughput is a much more positive
strategy for a firm than cutting costs, with the first directing attention towards earning more money with existing assets and the second implying a possible reduction in headcount.

7.5 SPEED LOSS PROGRAMME AND RESULTS

An understanding of the potential of addressing speed loss at the insulation company came after the widespread implementation of Overall Equipment Effectiveness (OEE), a measure used to identify losses on production lines, across factories in 2017. As discussed in Section 6.2, the insulation company struggled to determine the ideal throughput targets per product on each line due to shifting bottlenecks and high process variation, particularly for small batches. A team of operations analysts from headquarters working with representatives of each factory determined throughput targets per product using historical data. The analysts and factory representatives then created visual controls to monitor the gross throughput with respect to the established speed targets of the process live in the control room, with the operators documenting the reasons that speed targets could not be met for each batch. Factory management set targets for reduction of speed loss along with headquarters, and headquarters tracked the progress and capacity gains monthly.

While a large gain in capacity has been experienced simply by setting ambitious throughput targets on the production lines at the insulation company, the results from this thesis informed operational efforts in identifying the causes of speed loss and the magnitude of their impacts. The efforts to reduce speed loss led to a 3-5% capacity increase on key production lines during the project period, with potential remaining in the global production network through further addressing speed loss.

7.6 PRODUCTION SCHEDULING CHANGES AND RESULTS

One initiative pursued by the insulation company to exploit the operational benefits of reduced PV was to increase the lengths of production runs on the main production lines at the insulation company. Due to this initiative, a reduction in total changeover waste was seen in 41% of the company’s production lines in 2018 compared to 2015, allowing these lines to dedicate more capacity for creating saleable product. An additional initiative to improve product sequencing for additional capacity gain is being implemented in the factories as well.

Based on the findings from Section 6.3 regarding the use of product wheels for production scheduling at a baked goods manufacturing company, a pilot to test product wheels on one line at the insulation company was also designed and carried out from June to August 2017. The researcher facilitated a workshop with the production manager, supply chain manager, production planning team and an operations specialist to create a weekly production cycle based on the product wheel approach (King, 2009). Using the developed product wheel (shown in Figure 7-5), frequently produced products were scheduled only once per week, and similar products were clustered on specific weekdays to minimise changeover waste. The product wheel was
tested on a single production line for four weeks. One week of data was excluded from the evaluation due to a technical issue with the production line.

Figure 7-5 Product wheel at the insulation company

During the three-week period in which the product wheel was used for scheduling, the saleable throughput of the production line increased by 1.2% compared to the same period in the previous year. The longer batch sizes and optimised sequencing of the product wheel reduced the number and difficulty of changeovers occurring on the line, thereby reducing waste. In addition, no orders were unfulfilled due to lack of stock; however, some orders were delayed due to challenges with warehouse staff retrieving orders due to the increased cycle stock. Factory management was pleased with the increased throughput result but did not implement the product wheels permanently due to constraints on warehouse space for storing the large production batches.

The results of the pilot were shared with supply chain directors from other BUs at the insulation company in October 2017. During this meeting, best practices for production scheduling, stock planning and lead time adjustments were determined and are now implemented by the supply chain departments of each BU. Increasing run length and improved sequencing in the production schedule has been calculated to improve throughput by 1-2% across factories.
8 Discussion

‘The ability to simplify means to eliminate the unnecessary so that the necessary may speak’. Hans Hofmann

This section discusses the thesis findings in relation to the PV management and OM literature.

8.1 Product variety’s negative operational impact and mechanisms

In response to RQ1, the systematic literature reviews in Studies A and B have identified strongly negative PC⇒OP relationships for time and cost performance, while the evidence for quality and delivery performance was less clear but slightly in favour of a negative relationship (Moseley, Hvam, et al., 2017; Trattner, Hvam, Forza, et al., 2019). The results show that a plethora of PC and OP measures have been utilised by the research community, and the author proposes a grouping of PC measures based on their shared characteristics. When analysing nearly identical OP measures, the relationships identified can differ depending on the PC measure utilised. Findings from Studies C-E in Section 5 also help to answer RQ1 question, showing the largely negative influence of increased PV on process productivity via more complex production scheduling and the imposition of bottlenecks on the line (Moseley et al., 2016; Moseley, Myrodia, et al., 2017; Trattner and Hvam, 2018).

In addition to uncovering the negative direction of the PC⇒OP relationship, Studies A and B have also revealed the mechanisms behind the relationship, namely demand uncertainty (Abernathy et al., 2000; Fisher and Ittner, 1999; Koh et al., 2005; Vilas and Vandaele, 2002), the degree of similarity between products (Brahm et al., 2017; Busogi et al., 2017; Wan, 2016; Wan et al., 2012) and the extra coordination costs of handling additional and more complex product variants in production and in the supply chain (Ahmad and Shroeder, 2001; Jacobs and Swink, 2011; MacDuffie et al., 1996). The role of coordination costs in the PC⇒OP literature is in line with other OM literature discussing the complexity costs that arise from a complex product offering (Götzfried, 2013; Hvam et al., 2019; Myrodia, 2016; Wilson and Perumal, 2009). The findings are also in line with manufacturing strategy literature, which discusses the superior OP of ‘focused factories’ over factories producing a wider product mix (Skinner, 1974). The influence of the degree of similarity between products is not clear based on the literature set, with some authors arguing that adding variety similar to the existing assortment leads to better OP (Brahm et al., 2017; Wan, 2016; Wan et al., 2012) and others arguing the opposite (Busogi et al., 2017). This is an area of potential future research.

This literature study is considered novel in relation to existing literature as it is the first to attempt to synthesise empirical findings relating to the PV/PC⇒OP relationship in a structured fashion. Other literature reviews on increased PV do not emphasise the operational effects, focusing more on the market-related implications of greater PC or on the methods by which
the negative effects in operations can be managed (Brun and Pero, 2012; ElMaraghy et al., 2013; Ramdas, 2003). This thesis, together with Studies A and B, answers the call for more research on how variety impacts the manufacturing system and resulting production costs (Stäbli et al., 2011; Xia and Rajagopalan, 2009).

8.2 PRODUCT VARIETY’S IMPACT ON PROCESS PRODUCTIVITY AT THE INSULATION COMPANY

The negative impact of PV on process performance at the insulation company is undeniable in Studies C-E, which are described in Section 5. The influence of PV on production is shown to negatively affect process productivity, acting as a moderating variable in the PV → productivity relationship. The magnitude of this impact is reflected by the 5-8% loss in process productivity when producing in small batches. An additional 4-12% loss of process productivity was identified when products are scheduled in a suboptimal sequence on the production lines (Moseley et al., 2016; Moseley, Myrodia, et al., 2017; Trattner and Hvam, 2018). One additional finding from Study C is that smaller batch sizes are related to increased variability in process productivity. This finding prompted the more holistic exploration of process productivity drivers in Study E, where the inclusion of more process variables contributed to a significantly higher model fit than the analyses in Studies C and D. It is hypothesised that the high variability could also be due to measurement error, but this is not straightforward enough to determine.

The major contribution of this section is the empirical investigation of the influence of PV on process productivity in a non-standard process industry manufacturing context. The analyses from four insulation production lines present a process industry manufacturer utilises a hybrid system of both continuous and assembly line processes that are tightly coupled and automated from end to end. Due to the tight coupling, the process is highly efficient with almost no work-in-process inventory or waste in material handling, but it is also highly sensitive to changes in batch size, product changeovers and the sequencing of products. The effect of production planning variables on the productivity of high-volume manufacturing processes is described in the literature (Anderson, 1995; Berry and Cooper, 1999; ElMaraghy et al., 2013), but a case of such small batch production within a process industry firm is not presented. For the production line examined in Study C, 75% of the batches ran for less than three hours and consumed 50% of the total processing time for the product families examined. The regression coefficients in Studies C and D show that these small runs are disproportionally affected by suboptimal production sequencing, further eroding OP. Unlike the chemical producer examined by Berry and Cooper (1999), which had a minimum batch processing time of four hours, short batches are the daily reality for the insulation company, a reality that challenges common knowledge regarding how to operate within the process industry. As the demand for PV continues to increase, this new state of small batch operations for highly integrated manufacturing systems in the process industry could become more ubiquitous and could require new methods for understanding the higher variability in process productivity for small batches. The speed loss analysis framework presented in Section 6.2 is one such method that aims to
understand the sources of process productivity variability, but additional methods and research are needed.

Across all insulation lines examined in this thesis, the planning of PV was seen to affect the cost of PV. The findings suggest that process industry companies focusing primarily on customer-focused variety creation activities (Ramdas, 2003) should increase their emphasis on production scheduling to prevent diminishing OP. None of the PV management frameworks discussed in Section 2.4 explicitly lists production planning as an important initiative in managing the PV→OP relationship, but it could be argued that it is contained within the ‘flexibility strategies’ of Silveira’s (1998) framework in Figure 2-3. In future PV management frameworks, the researcher proposes that production planning be explicitly stated as a strategy for mitigating PV’s negative effects in process industries based on the findings of this thesis.

Individual product features (e.g. density, thickness) have also been found to impact process productivity, demonstrating the necessity of understanding the product-process interactions in a manufacturing system (Myrodia, 2016; Wilson and Perumal, 2009). Other authors have found that using detailed variety measures, such as product thickness or model mix complexity, has allowed for a more context-rich view of PV’s impact on OP for individual production systems (Anderson, 1995; MacDuffie et al., 1996). While the detailed PV measures are difficult to generalise across studies, they can provide valuable insights to operations managers regarding which variety imposes an additional burden to a production system.

PV has also been found to affect process productivity through the creation of mechanical bottlenecks on the line to achieve specific product features (e.g. a product with a certain feature requires a downstream process to run at a lower speed, causing upstream processes to slow down). This effect was quantified per product feature, with some features having no effect, some having a negative effect (e.g. lower density and thickness) and one feature having a positive effect (i.e. fleece application). Non-mechanical bottlenecks, or causes for reduced speed that are not related to equipment constraints, arose in the unavailability of recycled waste (an upstream process bottleneck when recycled waste material is unavailable) and product quality requirements (a downstream process bottleneck if the specifications of the product are stringent, requiring the speed of the upstream process to be reduced in the event of a quality issue).

The results from this study can inform PV decisions on capacity constrained lines, help supply chain managers improve production plans and assist production managers in targeting the greatest sources of lost production speed and capacity. The researcher acknowledges that maintaining an ideal production sequence may not always be achievable due to the short lead times, warehouse constraints, last minute order changes and other factors; however, efforts to cluster similar product groups, to reduce last minute order and schedule changes and to implement frozen scheduling periods could help reduce the number of out of sequence runs, thereby improving overall process time productivity. Though the magnitude of the effect of PV through planning and quality variables is not as substantial as it is for other variables on the lines analysed in Study E, the PV-related variables still present untapped potential for capacity and productivity improvements at the company. Where it is not possible to improve the process
productivity for a certain product, the reduced OP can be passed on to the market in the form of higher pricing or longer promised lead times. The researcher also acknowledges that the impact of PV could be lower for other production systems within the process industry.

8.3 METHODS TO BETTER MANAGE PRODUCT VARIETY AND ITS EFFECTS IN PROCESS INDUSTRIES

Section 6 demonstrates the utility of three methods for managing the PV→OP relationship in two different process industry settings: the product portfolio optimisation model based on substitution to enhance the company’s profitability, the framework used to analyse and to quantify the causes of speed loss to draw managerial attention to the areas of highest improvement and the product wheels for production scheduling. Two of these methods, the product portfolio optimisation method and the speed loss framework, are novel to the research community. The portfolio tool is new because it incorporates elements of product substitutability and linked revenue. The speed loss framework is novel because it fills a gap due to the lack of Lean and TPM methods addressing the needs of the process industry, where determining the relative impact of the process variables’ impact on productivity is not straightforward.

The three methods demonstrate the abilities to increase profitability, decrease inventory and changeover costs and drive throughput improvement initiatives at process industry firms producing high PV. The improvement potential identified includes a 1-3% increase in CM, a 6% increase in production throughput by removing causes of speed loss and a 23% reduction in changeover and inventory costs at the firms studied. An additional benefit of the three methods is the increased automation of resource intensive, mental processes and the decision support provided to operations managers and product managers. As the three methods address different functional areas within an organisation, nothing prohibits a company from incorporating all three methods into their standard business processes to achieve the maximal potential benefit.

For the research community, the first method presents one way by which product substitution can be accomplished while considering product profitability and linked revenue between products. A novel approach has been developed to assess possible product substitutions, including an index to calculate the degree of similarity between two products based on their attributes and other adjustable parameters representing the degree of risk the company is willing to take regarding product substitutability. The MIP model presented for portfolio optimisation presents a step forward in optimising a product portfolio while incorporating the concepts of substitutability and linked revenue, saving the company time and increasing the portfolio’s profitability. Ample models for optimising the profitability of a product portfolio are discussed in the literature (Denton et al., 2003; Ramdas and Sawhney, 2001; Singh et al., 2006; Sobreiro and Nagano, 2012), but linked revenue and substitutability are not addressed. The models that do address substitutability (Huang et al., 2011; Inderfurth, 2004; Kök and Fisher, 2007) do so in relation to order fulfilment when stock is depleted rather than in relation to reducing the portfolio breadth, as is done by the presented model. The 1-3% potential CM increase from using
the presented model is modest compared to others found in the literature, which have demonstrated increases in profit ranging from 5% (Ramdas and Sawhney, 2001) to 50% (Kök and Fisher, 2007). The model presented could be refined by placing upper bounds on the demand for certain products to generate more reliable and believable forecasts for product managers and by placing capacity limits on the resources required for certain products, as has been described in the literature (Singh et al., 2006; Sobreiro and Nagano, 2012).

An additional question regarding the optimisation model involves the extent to which it can be widely implemented in businesses. Only companies with a skilled workforce knowledgeable of OR methods and with access to solving software would be able to regularly run the optimisation model. Perhaps the largest effort to make when implementing such a model in practice would be managing the perceptions of the model and its inbuilt assumptions held by product managers and other decision makers at a company.

The second method presents a novel framework to empirically assess causes of lost production throughput and to quantify them for process industry manufacturers, extending the more experiment-driven approaches in existing literature (Benjamin et al., 2015; Nakajima, 1989) through an advanced regression analysis. The quantification of speed loss causes helps to prioritise the causes of speed loss for improvement. High variability in the insulation production process has been observed during this research, inspiring the development of the framework to identify the causes of variability. The importance of using data to identify sources of variance has been described in the literature (Christensen et al., 2007) and is a central theme of the just-in-time approach (Shingo, 1989; Zipkin, 1995), indicating that the framework is relevant beyond the studied case company. While PV is targeted specifically as a source of variation in Studies C and D, it is concluded that a more holistic assessment of variability drivers is needed. In the PV management literature, random variation has been described as ‘more pernicious’ than the impact of PV (Fisher and Ittner, 1999, p. 785), suggesting that the influence of PV should not be studied in isolation when assessing OP but along with other influential variables. In Study E, where the framework from Study G is applied, PV is found to significantly contribute to process productivity variations at the insulation company; however, PV is not the largest source of variation identified (Trattner and Hvam, 2018). In determining the impact of PV, it is important for researchers to account for other operational factors that may be relevant to operations managers seeking ways to increase production capacity and to reduce costs.

The discussion of the third method presented, the product wheel, contributes to knowledge through the further testing and validation of the product wheel as a production scheduling method for a process industry firm (i.e. a baking company). The case study revealed that the method has strengths in standardising operations but may be more suitable for companies with a low variety level because the heuristic approach became cumbersome to implement for a line producing 84 products. The product wheel is a heuristic approach proven to work in simulations of the baking company described in this thesis, but the product wheel was not implemented at the baking company; however, the implementation of the product wheel at the insulation company is discussed in Section 7.6 and is shown to improve process productivity by 1.2%. Other
results have shown that the product wheel is a good method for scheduling in low-variety contexts, such as for a chemical manufacturer (Wilson and Ali, 2014) or a polymer manufacturer (Cooke and Rohleder, 2006), by helping the companies achieve mix flexibility.

Despite the demonstrated utility of the product wheel, process industry firms operating with high PV and sequence-dependent changeovers should consider implementing OR models for production scheduling (Trattner et al., 2018). Existing production scheduling algorithms tailored for process industry manufacturers include steel melt and batch scheduling (Balakrishnan and Geunes, 2003; Naphade et al., 2001; Tang and Huang, 2007), algorithms developed for the food industry, such as Excel-based decision support systems (Akkerman and van Donk, 2008), and OR methods developed for the food industry (O’Reilly et al., 2015; Soman et al., 2007).

While the methods presented have been shown to be relevant for process industry manufacturers, they do not constitute a comprehensive set of PV management methods for process industry manufacturers. Other methods, such as using more advanced methods for production scheduling (Balakrishnan and Geunes, 2003), achieving mix flexibility on production equipment (Bengtsson and Olhager, 2002) and Lean manufacturing (MacDuffie et al., 1996; Shingo, 1989), would also be beneficial. Incorporating additional methods from the marketing domains to align the portfolio offering with customer needs is another area in which a method would be beneficial (Myrodia, 2016; Ramdas, 2003).

8.4 LEVERS FOR REDUCING PRODUCT VARIETY AT THE INSULATION COMPANY

The longitudinal case confirms the effectiveness of some of the PV management levers identified in the literature and adds two additional perspectives. The first new perspective offered by this case is the importance of the sales distribution channel, or the various methods of selling products within the same firm. At the insulation company, it was observed that different product segments were sold using either off-the-shelf sales or project sales channels, with off-the-shelf products being quite standardised with limited variety and project products being more customisable for the customer. These two sales distribution channels exist within the same BU and were found to affect the PV management approach. While some research proposes the thorough understanding of customers and competitors when managing PV (Myrodia, 2016; Silveira, 1998), there is no discussion of the relevance of the sales distribution channel in the PV management literature to the best of the researcher’s knowledge.

A second insight arising from the case study is the importance of the market situation and resulting capacity utilisation of key production assets at the insulation company to inform the appropriate PV management approach. Factories constrained on capacity at the insulation company were more open to PV reduction activities because every extra ton that could be produced by eliminating a changeover or removing an unprofitable product could be sold. Under-utilised factories and factories in growth markets did not foresee the same operational benefits from
PV reduction. This finding is especially key to PV management in process industries with expensive fixed assets that should be fully utilised to maintain low prices for the products (Abdulmalek et al., 2006). Some studies anecdotally discuss the importance of capacity utilisation in determining the PV management strategy (Götzfried, 2013; Quelch and Kenny, 1995), and other studies show that buffer capacity can mask the influence of PV on OP (Fisher and Ittner, 1999; Ramdas, 2003); however, the literature does not discuss how the dynamic variables of capacity utilisation and the market situation can impact the method used to manage PV.

In addition to the new perspectives stated, this case provides evidence supporting other PV management levers discussed in the literature. The importance of clearly communicating the business benefits from PV reduction was observed in the insulation company as it specifically reduced PV to increase throughput on constrained production lines. Perumal and Wilson (2017) suggest that organisations target specific, measurable improvements in business performance, such as fixed cost reduction or service level improvements, when reducing PV. This suggestion is further supported by another research study that shows that companies using clear PC targets realise higher levels of profit from their product portfolios (Closs et al., 2008).

The cross-functional review of the product assortment shown in Figure 7-3 was also fundamental to the PV reduction and improvement of profitability at the insulation company. Including multiple stakeholders in the review of the product assortment has been cited as an enabler of effective PV management in the literature (Closs et al., 2008; Götzfried, 2013; Wilson and Perumal, 2009). In the analysis of six in-depth case studies, it was found that ‘business units that employ more rigorous, cross-functional review processes throughout product development and lifecycle management achieve more profitable levels of product portfolio complexity’ (Closs et al., 2008, p. 605). While a rigorous comparison of the business processes used for PV reduction across business units at the insulation company was not performed, it was evident that business units that implemented a cross-functional review earlier in the project period made visible changes to the product assortment earlier as well.

The one-in-one-out policy (the process of removing a product after adding a product to the portfolio) used to maintain lower PV levels in the case study has support from academic literature. The importance of implementing proactive means to control the creation of PV has been discussed by multiple authors (Götzfried, 2013; Hansen et al., 2012; Silveira, 1998). One quantitative study shows that companies that added products and removed products in the same year increased total factor productivity compared to companies that did not change PV or only added or dropped products (Alvarez et al., 2016), providing support for the one-in-one-out rule. The researcher acknowledges that this simple rule of removing a product for every new product launch may not be a viable strategy under certain circumstances (e.g. expansion into new markets, high growth product segments for which production capacity is expanded); however, for companies serving established market segments with the existing supply chain network, the one-in-one-out rule may be more effective than others for supporting profitable PV management. The effectiveness of the one-in-one-out rule is a potential area for further research.
9 CONCLUSIONS

This thesis presents the effects of increased PV on the performance of operations in the process industry and the methods by which the effects can be managed. Eight conference papers and journal papers along with one unpublished longitudinal case study of PV reduction at an insulation manufacturer serve as the empirical body of this thesis and highlight a peculiar case of high-variety, small batch production within the process industry. The studies address three research questions, assessing (1) how PV impacts OP in industrial companies, (2) the magnitude of the impact of PV on process productivity in the process industry and (3) the methods that can be used to manage PV and its effects in the process industry.

First, strong, detrimental relationships between PV and both cost and time performance have been identified through two systematic literature reviews. Slightly negative relationships have been identified for quality and delivery performance; however, the results are more inconclusive, and the relationships have not been studied as extensively as time and cost performance. The negative relationships arise between PV and OP measures due to the increased coordination costs required in the value chain to deliver greater PV and complexity to the customer, increased demand volatility and the degree of dissimilarity between products. As this literature review covered all manner of production and supply chain companies, the results can be reasonably extended to all industrial companies.

Next, three quantitative studies have revealed that PV is correlated with negative process productivity at an insulation manufacturer. PV is found to affect process productivity through the imposition of mechanical bottlenecks, more stringent quality specifications and material shortages as well as through production scheduling practices. The insulation company assessed is a special case within the process industry that diverges from the traditional modus operandi of process industry companies by using a tightly coupled, hybrid production system that produces high levels of PV in relatively small batch sizes. This mode of operation may potentially become more widespread as demand for new product variants and customised products continues to permeate the process industry, indicating further industrial relevance of the case of the insulation company.

Third, three methods have been identified and tested for managing PV and its effects for process industry manufacturers, including a product portfolio optimisation tool based on product substitution, a framework for analysing speed losses on production lines and the product wheel used for production scheduling. These methods have proven to effectively mitigate the decreased profitability, reduced process productivity and increased operational costs that can result from increased PV levels. The internal validity of the findings is augmented by the multiple data sources utilised in all stages of the research (e.g. text from production logs, semi-structured interviews, production databases), which allowed for triangulation. Utilising multiple case studies and quantitative studies of a similar firm allowed for a comparison of quantitative analysis results, which corroborated each other.
Finally, a longitudinal case study of PV reduction at an insulation manufacturer revealed additional levers by which PV can be managed and reduced. These levers include the clear communication of the anticipated benefits from PV reduction, the implementation of product portfolio reviews using cross-functional teams and the proactive control of variety levels. The case study also reveals the importance of considering the sales distribution channel and the capacity utilisation of key production assets when developing the PV management approach.

The intentional selection of case companies in the process industry that experience high PV levels supports the reliability of the results presented. Because cases were only taken from an insulation company and a producer of baked goods, both of which operated continuous flow production lines, the findings from this thesis can be easily extended to other process industry companies operating with continuous flow production lines; however, some of the methods can be extended to other industrial companies without consideration of the production system utilised (i.e. the product portfolio optimisation method).

9.1 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Regarding the limitations of this thesis, this work largely focuses on the operational perspectives of PV management, giving only minor attention to commercial perspectives, such as product substitution. This was done deliberately to focus the scope of the thesis; however, knowledge of the market demand and customer behaviour are required to obtain a holistic view of the product assortment before it can be managed effectively. In addition, the impact of PV on process productivity (i.e. throughput) is heavily assessed in the quantitative studies, while other measures of OP, such as lead time, delivery reliability and product quality, are not assessed.

Regarding applicability to the process industry, most of the case companies assessed are insulation producers that operate a hybrid continuous flow and assembly line production process (Hayes and Wheelwright, 1979), but there is much more variegation in the broader process industry where continuous and batch processes are also utilised (Crama et al., 2001). It is therefore an opportunity for future work to closely examine batch processing and the applicability of the presented methods to this area.

Many of the results from the regression analyses are interpreted as causal based on the physical observation of the machines and the logical analysis of possible mechanisms to support a causal relationship. Despite these measures, it is possible that the statistical relationships identified in these studies may not be causal (Hayes, 2013).

One area for potential research is investigating the organisational and technological variables that influence the PV→OP relationship and the effectiveness of PV management initiatives. The cultural and management style differences across the BUs at the insulation company seemed to be related to the varying levels of success in reducing PV in this project, but this was not studied in detail in this thesis. Other opportunities for research are investigating the
effectiveness and delimitations of the one-in-one-out rule for managing PV, the importance of capacity utilisation and the importance of the sales distribution channel in relation to other PV management practices. There is also room for additional quantitative analyses of more extensive survey data from a larger sample of process industry manufacturers to better understand PV’s impact on operational and financial performance.

9.2 Contributions to theory
Contributions to theory from this thesis include a greater depth in the understanding of the relationship specifically on this topic and provides directions for future research for academics. This thesis also contributes to the literature through the quantification of the impact of PV on process productivity in a unique operational context within the process industry: that of high variety, small batch production on a hybrid continuous flow assembly line process, which diverges from the diagonal of the traditional product-process matrix (Hayes and Wheelwright, 1979).

Two novel methods are presented for optimising the portfolio and for assessing speed losses on process manufacturing lines, which contributes to the academic literature. A third method for production scheduling has also been tested and evaluated for applicability to the food industry. Finally, a longitudinal case study of PV reduction provides support for PV management levers identified in the literature and reveals the importance of considering the sales distribution channel and the capacity utilisation of the equipment when managing PV in process industries.

9.3 Contributions to practice
For firms operating in the process industry, this thesis provides clarity regarding what operations managers can expect in situations involving increased PV. Proven methods and levers from actual cases for managing PV and its operational effects, including the importance of production planning, the assessment of process variability and various portfolio optimisation practices, have also been provided. As this thesis was carried out in collaboration with a company in which PV management and reduction methods were developed, implemented and proven financially and operationally beneficial, this thesis can be argued as already demonstrating advanced industrial practice in a process industry firm. Furthermore, the findings of this thesis have been presented in six lectures at the Technical University of Denmark for Masters and doctoral students, in one Danish manufacturing network meeting, and at four other firms in Denmark with positive feedback regarding the work’s relevance to other industries.
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APPENDIX

The papers referred to in the thesis are included in this section. A cover page stating relevant details of the manuscript and the submission status is included before each article.
<table>
<thead>
<tr>
<th><strong>STUDY A</strong></th>
<th></th>
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<td><strong>Paper title</strong></td>
<td>Product variety, product complexity and manufacturing operational performance: a systematic literature review</td>
</tr>
<tr>
<td><strong>Authors</strong></td>
<td>Alexandria (Moseley) Trattner, Lars Hvam, Zaza Nadja Lee Herbert-Hansen and Christian Haim Raben</td>
</tr>
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<td><strong>Paper type</strong></td>
<td>Conference paper</td>
</tr>
<tr>
<td><strong>Outlet</strong></td>
<td><em>Proceedings of the 24th International EurOMA Conference</em>, Edinburgh, Scotland, 2017</td>
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<td><strong>Paper status</strong></td>
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Product variety, product complexity and manufacturing operational performance: A systematic literature review

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Abstract

Manufacturing in the twenty-first century has been wrought with the struggle to satisfy the rising demand for greater product variety and more complex products while still maintaining efficient manufacturing operations. However, the literature lacks an overview of which operational performance measures are most affected by increased variety and complexity. This study presents a systematic literature review of the recent scholarly literature on variety, complexity and manufacturing operational performance (MOP). Results show that product variety has a consistently negative relationship with MOP across different time, cost, quality and flexibility measures while product complexity lacks evidence of strong relationships with MOP measures.

Keywords: Product variety, Complexity, Performance

Introduction

Manufacturing in the twenty-first century has been wrought with the struggle to satisfy the rising demand for greater product variety and more complex products while still maintaining efficient operations. Scholars have discussed how to optimize production in the face of rising customer demands for custom product over the past 20 years from different perspectives (Berry & Cooper 1999; da Silveira 1998; MacDuffie et al. 1996). Concepts such as flexible manufacturing systems, Lean, setup time reduction, and production scheduling have all been discussed as solutions to help manufacturers cope with the rising demands on their facilities (Balakrishnan & Geunes 2003; da Silveira 1998; MacDuffie et al. 1996).

Among all the descriptions of techniques, there has yet to be presented a comprehensive overview of the literature assessing the relationships between product variety and product complexity and different measures of manufacturing operational performance. Such an overview would reveal where manufacturers can expect to see the impact of increased variety and complexity.
in their products on their internal performance measures such as labor hours per unit and external performance measures, such as delivery service level and flexibility towards customers. Further, the data would reveal that factors that allow manufacturers to produce as efficiently as possible while still maintaining a high product mix in different industries. In this study, we undertake to meet this need using a systematic literature review.

The research question guiding this study is: what is the impact of product variety and product complexity on manufacturing performance? As the two terms have been used interchangeably in the literature, both “product variety” and “product complexity” are considered in this study along with related terms, such as “mass customization” and “product diversity.” For the purposes of this study they will be distinguished. Product variety (PV) will refer to number of products produced or components used in production (Berry & Cooper 1999). Product complexity (PC) will refer to the level of complexity of the products produced at the firm (Bortolotti et al. 2013; Caniato & Größler 2015).

Operational performance has been defined in previous work as unit manufacturing cost, quality, speed of new product introduction, flexibility, and delivery dependability (Ferdows & De Meyer 1990). Within this study, the performance of manufacturing processes is assessed and termed manufacturing operational performance (MOP) will be defined as measures of cost, time, quality, flexibility (or responsiveness) within the production environment at manufacturing companies, including productivity, which relates to time.

The objective of this research is synthesizing the relationships between PV, PC, and specific measures of MOP in recent scholarly literature and reveal directions for future research. This paper is structured as follows: first, the methodology behind the systematic literature review is presented, second, the analysis and coding of the articles is described and discussed, and last conclusions are drawn and future research is suggested.

Methodology
The systematic literature review approach proposed by Tranfield, et al. (2003) was used to conduct this study to obtain and unbiased and thorough search of the existing knowledge of the relationships between PV, PC, and MOP. Systematic literature review is an acknowledged method for ascertaining the key concepts within scholarly literature in the fields of medicine and management which typically consists of three phases: planning, conducting and reporting a review (Tranfield et al. 2003). In this study, a search string was developed to explore the body of literature regarding the three constructs of product variety, product complexity and manufacturing performance. Two literature databases SCOPUS and Web of Science were selected as they contain relevant management and engineering journals of high academic quality and cover different sets of journals.

To ensure a comprehensive and unbiased search, the search string has been developed through multiple iterations. The initial search string was constructed in collaboration with four researchers to ensure a broad perspective and reduce the risk of omitting key words and synonyms. Keywords were added to the search string through an initial literature search until the additional terms did not give any new results. An overview of the search strings used for each database is shown in Table 1. Search results were limited to journal articles written in English and published within the past 25 years.

To narrow the body of literature further and bring forward the most relevant works in the field, journal quality criteria were applied next. The journals must have scored in the first of second quartile of the SCImago Index in 2015 in operations management or related field (e.g. strategy and management) in order to pass through the quality screening. Next, abstract criteria were applied to the literature sample to identify articles which utilized the constructs of product variety, product complexity and manufacturing performance or similar. Only articles which utilized the terms for
PV, PC and MOP from the search strings as their key constructs were assessed for full text reading. The final selected articles were analyzed through a full text reading, concept mapping and synthesis as detailed by Rowley and Slack (2004). The result of this process is summarized in Figure 1 where an initial search result of 955 articles from both databases was reduced to 30 articles for full text reading and coding.

Table 1 - Article search strings by database

<table>
<thead>
<tr>
<th>Database</th>
<th>Search String</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scopus (Elsevier)</td>
<td>(TITLE-ABS-KEY (&quot;product customisation&quot; OR &quot;mass customisation&quot; OR &quot;product diversity&quot; OR &quot;product vari**&quot; OR &quot;complexity management&quot; OR &quot;product divers**&quot; OR &quot;product proliferation&quot; OR &quot;product complexity&quot; OR &quot;product architecture&quot; OR &quot;product portfolio complexity&quot;) AND TITLE-ABS-KEY (&quot;production performance&quot; OR &quot;manufacturing performance&quot; OR &quot;operational performance&quot; OR &quot;production impact&quot; OR &quot;manufacturing impact&quot; OR &quot;operational impact&quot; OR &quot;manufacturing flexibility&quot; OR &quot;productivity&quot; OR &quot;throughput&quot; OR &quot;order initiated production&quot; OR &quot;continuous production&quot; OR &quot;flow production&quot;) )</td>
</tr>
<tr>
<td>Web of Science (Thomson Reuters)</td>
<td>((&quot;product customization&quot; OR &quot;product customisation&quot; OR &quot;mass customization&quot; OR &quot;mass customisation&quot; OR &quot;product diversity&quot; OR &quot;product variability&quot; OR &quot;product variation&quot; OR &quot;complexity management&quot; OR &quot;product diversification&quot; OR &quot;product proliferation&quot; OR &quot;product variety&quot; OR &quot;product complexity&quot; OR &quot;product architecture&quot; OR &quot;product portfolio complexity&quot;) AND (&quot;production performance&quot; OR &quot;manufacturing performance&quot; OR &quot;operational performance&quot; OR &quot;production impact&quot; OR &quot;manufacturing impact&quot; OR &quot;operational impact&quot; OR &quot;manufacturing flexibility&quot; OR &quot;productivity&quot; OR &quot;throughput&quot; OR &quot;customized production&quot; OR &quot;customised production&quot; OR &quot;order initiated production&quot; OR &quot;continuous production&quot; OR &quot;flow production&quot;) )</td>
</tr>
</tbody>
</table>

Figure 1 – Article selection process
Analysis
The thirty articles selected for full text review were analyzed by publication date, industry, and coded based on the nature of the relationships shown between PV, PC, and MOP. As can be seen in Figures 2, there has been an interest in the impact of PV and PC on MOP since the late 1990s but with a relatively low interest level, seen as only 1-4 articles published per year on the topic. Interest appears to have risen in the last decade with at least one journal publishing an article on the topic every year since 2009. Results are limited to the last 25 years of research due to database restrictions. It is expected that further research would result in another peak in article publication in the 1980s around the time of World Class Manufacturing and the proliferation of Lean manufacturing practices.

![Figure 2 – Articles published which discuss the relationships between PV/PC and MOP showing (a) accumulated articles per year and (b) absolute articles per year](image)

The research detailing the relationship between PV, PC and MOP span a range of industries, as can be seen in Table 2. To classify the industry of the cases and examples used in the articles, the Thomson Reuters Business Classification scheme was applied (Anon 2017). The articles which used single cases or examples to illustrate their purpose are counted within one of the industry codes. Articles with multiple cases are counted in the code “Mixed” and articles without a case or with cases which had no distinct industry group are counted in the group “N/A”.

<table>
<thead>
<tr>
<th>Thomson Reuters Industry Code</th>
<th>Number of Articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>51101010 Commodity Chemicals</td>
<td>1</td>
</tr>
<tr>
<td>52102010 Industrial Machinery &amp; Equipment</td>
<td>1</td>
</tr>
<tr>
<td>52102020 Heavy Machinery &amp; Vehicles</td>
<td>1</td>
</tr>
<tr>
<td>53101010 Auto &amp; Truck Manufacturers</td>
<td>2</td>
</tr>
<tr>
<td>53101020 Auto, Truck &amp; Motorcycle Parts</td>
<td>2</td>
</tr>
<tr>
<td>53202030 Footwear</td>
<td>2</td>
</tr>
<tr>
<td>53203010 Homebuilding</td>
<td>1</td>
</tr>
<tr>
<td>54102020 Food Processing</td>
<td>1</td>
</tr>
<tr>
<td>57106020 Phones &amp; Handheld Devices</td>
<td>1</td>
</tr>
<tr>
<td>Mixed (e.g. survey research)</td>
<td>11</td>
</tr>
<tr>
<td>N/A (e.g. generic mixed model assembly lines)</td>
<td>7</td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>30</strong></td>
</tr>
</tbody>
</table>
The results of the industry analysis show a good representation of the automotive, footwear and machinery industries, accounting for 8 of the 12 articles which were able to be classified by industry code. As these were some of the first industries to experience mass customization, it is logical that they should be represented in the list. Under represented in the list are cases of companies operating within the process industries, with only two articles represented from the chemicals and food industries.

**Literature Coding**

In the full text literature review, relationships between PV and MOP and PC and MOP were identified and mapped into an overview in Table 3. A relationship qualified for inclusion if it was observed and discussed within the article. For case study research articles, the relationships emerged from the empirical data gathered from the case company. For the quantitative research articles, the positive and negative relationships included in Table 3 were the statistically significant relationships found in the analysis. The relationships discussed in conceptual and methodological papers were included only if a numerical example was provided or previous work was cited to support the claim.

The relationships were coded first according to the four MOP measures of time, cost, quality, and delivery and second according to the direction of the relationship: positive, no relationship, or negative. Positive relationships between PV and MOP (or PC and MOP) were defined as increasing time-based performance (e.g. increased throughput or efficiency, decreased cycle time, decreased lead time), decreasing cost of production or inventory, increasing quality, and increasing flexibility, delivery or responsiveness. Negative relationships imply the opposite relationships as the positive relationships. The category “no relationship” was included to categorize the articles which tested relationships but found them not to be significant nor present in the data.

The overview in Table 3 shows that PV and its impact on MOP has been studied more in the past 25 years than PC, with roughly three times more relationships identified for PV than PC. At a high level, it appears that PV has a consistently negative impact on MOP across the selected measures of performance while the impact of PC on MOP is slightly positive or not existing. This distinct difference between PV and PC suggests that these constructs be clearly distinguished when utilized in the literature as they have different effects on MOP. Examples supporting the relationships between PV/PC and MOP are discussed below.

<table>
<thead>
<tr>
<th>PV / PC</th>
<th>MOP Measure</th>
<th>Positive relationship</th>
<th>No relationship</th>
<th>Negative relationship</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV</td>
<td>Time</td>
<td>3</td>
<td>3</td>
<td>11</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>Cost</td>
<td>2</td>
<td></td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Quality</td>
<td></td>
<td>3</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>Flexibility</td>
<td>1</td>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>General MOP</td>
<td></td>
<td></td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Subtotal</td>
<td>5</td>
<td>6</td>
<td>20</td>
<td>32</td>
</tr>
<tr>
<td>PC</td>
<td>Time</td>
<td>1</td>
<td>2</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Cost</td>
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<tr>
<td></td>
<td>Quality</td>
<td></td>
<td>1</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Flexibility</td>
<td>1</td>
<td>3</td>
<td></td>
<td>4</td>
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<tr>
<td></td>
<td>Subtotal</td>
<td>2</td>
<td>7</td>
<td></td>
<td>9</td>
</tr>
</tbody>
</table>
Impact of PV → MOP

The overview in Table 3 clearly shows that the impact of increasing the number of units in production leads to reduced time-based MOP. This was directly observed or quantified in 11 instances within from the sample of 30 which were assessed with full text reading and is the most relationship with the highest frequency of discussion in the recent literature.

The impact of PV on time based performance came largely from the case study literature which shows that increased PV leads to reduced batch size, increased setup time, and reduced line speed, leading to decreasing efficiency and productivity. This was discussed in the automotive industry, footwear industry, chemicals industry, and general batch manufacturers (Barnett et al. 2004; Berry & Cooper 1999; Nandkeolyar & Christy 1992; MacDuffie et al. 1996; Gollop 1997; Nagarur & Azeem 1999; da Silveira 2006).

One interesting case showing a positive relationship between PV and time-based MOP was the case of a gearbox producer in the automotive industry which decreased lead time while increasing PV via use of smaller batches (ElMaraghy et al. 2009). A correlation analysis of survey results from UK manufacturers showed similar findings (Mapes et al. 1997). This comparison suggests that increasing PV could lead to decreased productivity or throughput in production, but shorter, more competitive lead times due to smaller batches and greater agility.

A few of the studies shows no relationship when quantifying the impact of PV on MOP, but this was due to the type of variety being assessed and nature of the company (MacDuffie et al. 1996; Fisher & Ittner 1999). MacDuffie et al (1996) showed that base model variety did not affect performance of an automotive manufacturer for all 70 automotive manufacturing plants assessed while the variety at the intermediate level of the product architecture (e.g. wire harness, engine type) did not affect productivity in companies which had Lean capabilities. his suggests that variety type and organizational capabilities moderate the effect of PV on MOP.

There is disagreement in the literature regarding the impact of PV on inventory costs, with some studies finding that increased PV leads to decreasing finished goods inventory (ElMaraghy et al. 2009; Macchion et al. 2016) and another study showing increased inventory costs due to variability in the production plant (Fisher & Ittner 1999). Besides the topic of inventory costs, there is consensus in the literature that increasing PV leads to higher costs in production (Mapes et al. 1997; Jacobs & Swink 2011; da Silveira 1998).

Regarding quality, the results in Table 3 show a slight negative relationship. PV led to decreasing quality in three studies of various manufacturer plants in the automotive, footwear, and mechanical products industries (Jacobs & Swink 2011; Macchion et al. 2016; da Silveira 1998). However, no relationship was found in a further three articles covering a similar span of industries (MacDuffie et al. 1996; Mapes et al. 1997; Fisher & Ittner 1999). The balance in the discussion between a negative relationship and no relationship suggests that there are moderating factors which affect the way PV impacts product quality, though these moderating effects were not investigated.

The relationship between PV and flexibility was found to be underrepresented in the recent literature with mixed findings, thus making it difficult to conclude on (Mapes et al. 1997; Salvador et al. 2007). A further study assessed MOP as a general construct comprised of weighted values of individual performance measures and found an overall negative impact of PV on MOP using panel data analysis of 3857 publicly traded firms (Kovach et al. 2015).

Impact of PC → MOP

The literature addressing PC shows that there is no strong relationship between the complexity of the products produced and any measure of manufacturing operational performance. No relationship was found between PV and efficiency, cost, quality, flexibility, nor responsiveness (Bortolotti et al. 2013; Caniato & Größler 2015) while two studies showed a positive impact of PC on costs and
responsiveness (Fan et al. 2016; Wang et al. 2012). MacDuffie et al. (1996) offers an interesting perspective on why there could be a lack of relationship between PC and MOP in their study of *model mix complexity*, or the complexity arising from the number of base models produced on a product line (MacDuffie et al. 1996). MacDuffie et al. states that production lines are typically built to handle the certain number of base models on the line, and thus they are able to cope with stress of product variations at the base model level without compromising operational performance (MacDuffie et al. 1996). Thus, it is not necessarily true the production lines which make more complex products should perform worse than production lines making simpler products because each line is designed to handle the required level of product complexity.

A conceptual paper revealed another potential reason for the lack of relationship between PC and MOP. When assessing the complexity of a set of products, Jacobs and Swink (2011) suggest that it is not the *multiplicity* (presence of many options for the same basic component) within a set of products that causes decreasing operational performance, but rather the *diversity* that causes the negative impact to performance. Returning to the comparison of a line making complex products to a line making simple products, this implies that it is the variability in PC or PV of a products coming down a line would cause the deviation in MOP, not the level PC or PV. This finding on the variability of PV was discussed in other papers in the analysis (Fisher & Ittner 1999).

In the many of the studies which proposed relationships, PC was operationalized as a combined measure of various answers from survey results (Bortolotti et al. 2013; Caniato & Größler 2015). While such operationalization is required for high level analysis with regression and structural equation modelling of vague topics such as complexity, these combined measures do not create a clear picture of how complexity within a products structure can impact production performance.

**Secondary relationships**
The articles selected for full text reading were further screened for secondary relationships and other factors with influence the relationship between PV and MOP and PC and MOP. Secondary relationships which were found within the 30 article sample include:

- Machinery flexibility (Berry & Cooper 1999; Comstock et al. 2004)
- Product modularity (Salvador et al. 2002; Kamrani et al. 2012; Vickery et al. 2015; da Silveira 2006)
- Organizational capabilities (e.g. organizational learning) (Jacobs & Swink 2011)
- Mass customization capability (Liu et al. 2012)
- Lean, quality programs and continuous improvement (MacDuffie et al. 1996; da Silveira 2006)
- Work station complexity (Wang & Hu 2010; Wong et al. 2015; Zhao et al. 2015)

These relationships should assessed further to understand the how much and in which contexts they influence the relationships between PV and MOP and PC and MOP.

**Conclusion**
The systematic literature review of the recent scholarly literature on variety, complexity and performance shows a distinct difference between the relationship between product variety and manufacturing operational performance and product complexity and manufacturing operational performance. In the final literature sample of 30 articles from the past 25 years of research, product variety showed a consistently negative relationship with MOP across the different time, cost, quality and flexibility measures while product complexity showed a lack of strong relationships with the MOP measures.
The discussion of the relationships show that PV and PC should be clearly distinguished when used in scholarly work as their effects are distinctly in manufacturing environments, across industries. Regarding the negative impact of PV on MOP, it was generally found that increased PV lead to decreased productivity but increased responsiveness (i.e. shorter lead time) due to the use of smaller batches. This tradeoff can be used by manufacturers when assessing production strategy for their manufacturing plants. Furthermore, a set of moderating variables which influence the relationships between PV and MOP and PC and MOP were identified, including machine flexibility, product modularization, production scheduling practices, organizational capabilities, mass customization capability, Lean, and work station complexity.

Future research topics include investigation of the effects of PC on MOP as this relationship was found to be under researched compared PV, investigation of the how moderating factors impact the relationships between PC and MOP and PV and MOP, and investigation into the relationships of PV and PC on MOP in the process industry.

References


**STUDY B**

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<th>Product complexity and operational performance: A systematic literature review</th>
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<tr>
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Product complexity and operational performance: A systematic literature review

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Abstract
This study presents a systematic literature review of the recent scholarly literature on product complexity (number, diversity, and interrelatedness of product variants and components) and operational performance (measured in cost, time quality, and delivery reliability), considering the manufacturing context as well as the mechanisms behind the relationships. The results show that product complexity has a consistently negative relationship with cost, time, quality, and delivery performance measures, though the relationships with quality and delivery performance are less clear.

Keywords: Product Variety, Product Complexity, Operational Performance, Manufacturing, Complexity Management

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Product complexity and operational performance: A systematic literature review

1. Introduction

1.1 Background

Increased competition, globalization, and increasing customer demand for unique products have led to a drastic increase in the number of product offerings in manufacturing firms (Bayus and Putsis, 1999; Quelch and Kenny, 1995; Silveira, 1998; Stäblien et al., 2011). Consumer packaged goods firms growing their stock keeping units (Quelch and Kenny, 1995), Philips expanding into 60 product categories by 2011, and LEGO doubling the number of unique brick types from 1997 to 2004 (Mocker and Ross, 2017) are just a few manifestations of the effects of increased product complexity on modern industry. This increase in product offerings can cause complexity in organizations, damaging operational performance as measured in labor costs, factory overhead costs, and productivity (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996; Mocker and Ross, 2017; Wilson and Perumal, 2009). Since operational performance and manufacturing strategy are keys to competitiveness and overall business performance (Fine and Hax, 1985), it is critical that manufacturing firms understand the impacts of complex product offerings on operational performance, such as time, cost, quality, and delivery. Understanding the impacts on lead time and delivery reliability is even more imperative now in the era of competing supply chains, in which companies must increase their flexibility towards the customer in terms of logistics, lead time, reliability, and variety (Christopher, 2000).

Previous studies on the impact of product complexity on overall firm performance have not focused on the effects on operational performance in manufacturing systems (Brun and Pero, 2012; ElMaraghy et al., 2013; Ramdas, 2003). Silveira (1998) offered a short review of literature on the operational impacts of product complexity, but it is constrained to dated studies from the late 1980s to early 1990s. A more recent review on product variety management emerged in 2013 and discusses management interventions intended to cope with increased product variants, but the exact impact of product complexity in the absence of interventions is not explored (Reis et al., 2013).

As the literature on the product complexity–performance relationship has accumulated, researchers have identified a set of strong linkages within the manufacturing and supply chain contexts; however, there has been little effort to synthesize the overall trends in this literature using a structured approach. As two authors studying production costs state, “the nature of [the product complexity-cost relationship] is not clear, and empirical evidence about whether and how production cost increases with variety is inconclusive” (Xia and Rajagopalan, 2009, p. 890). It is not known which operational performance measures provide conclusive evidence of a trend and which require further investigation. Furthermore, there is little understanding of how product complexity impacts different production system designs. The need for more work in this area is echoed by Stäblien et al. (2011), who stated that “in many ways we still have only a limited understanding of how variety impacts the manufacturing system, and how to counter this impact effectively and efficiently” (Stäblien et al., 2011, p. 351). To the best of our knowledge, there has been no comprehensive overview of the literature assessing the relationships between product complexity (PC) and measures of operational performance (OP).

1.2 Research Questions and Contribution

The objective of this research is to synthesize the relationships between PC and specific measures of OP in the recent scholarly literature and reveal directions for future research using a
structured literature review. Systematized understanding of which product complexity–performance relationships have conclusive evidence of a positive or negative tendency will form a basis of what is known and what needs to be explored further. Additionally, practitioners will benefit from knowing and anticipating the effects of increasing PC within their industry-specific manufacturing systems so they can plan appropriate interventions. Such an overview would reveal where manufacturers can expect increased PC to impact both internal and external performance measures, allowing a tailored management approach based on competitive priorities.

This article builds on a previous work by Trattner et al. (2017) and advances the method in the following ways. First, the search string was made more comprehensive to cover missing operational performance measures. Second, the study was expanded from process manufacturing systems to all types of manufacturing systems to increase generalizability. Furthermore, the terminology was made more succinct by referring to all product variety- and product complexity-related terms as product complexity. The authors believe these changes increase the relevance and simplicity of this article for the academic community as well as for practitioners.

In this study, we seek to meet the research need using a systematic literature review. Exploration of the literature is guided by a set of three research questions developed by the authors:

RQ1 Which PC → OP relationships are most supported by the literature?
RQ2 Which PC → OP relationships still need further investigation?
RQ3 What are the most explored/underexplored types of production in the literature discussing the PC → OP relationship?

The first and second research questions seek to identify the consolidated and fragmented areas of research on the PC → OP relationship to inform managers and guide future research. The third research question will contribute to better understanding the PC → OP relationships, considering the industry context and respective production systems. This set of research questions responds to the calls of Stäbli et al. (2011) and Xia and Rajagopalan (2009) for a synthesis of empirical evidence supporting the PC → OP relationships in different manufacturing systems.

1.3 Product Complexity

Defining constructs clearly is a necessary precursor to a systematic literature review. The term product complexity has no consistent definition in the management and engineering literature, making the operationalization of the construct difficult (Lindemann et al., 2010). Despite this lack of clarity, PC has been described in the literature as having many dimensions, including the number of components, the number of modules, the number of finished good variants in a portfolio, the number of interrelations between components, the commonality of products in an assortment, and the diversity of relations between components (Jacobs, 2013; Jacobs and Swink, 2011; Lindemann et al., 2010). In this literature study, PC will be an umbrella term covering measures of the variety, diversity, and interrelatedness of a single product or range of products in a production system. PC will also encompass related terms, such as product customization, product diversification, and similar terms. Product variety was also considered as the primary construct to study, but it was found to be an element of PC. Thus, PC was chosen for analysis.

1.4 Operational Performance

OP has been defined in previous work to include measures of unit manufacturing cost, quality, inventory turn, speed of new product introduction, flexibility, and delivery dependability (Ferdows and De Meyer, 1990; Filippini et al., 1998; Fine and Hax, 1985; Squire et al., 2006). Within this
study, the performance of manufacturing processes is assessed and referred to as manufacturing OP, defined as measures of cost, time, quality, and delivery reliability relating to the operations within manufacturing companies. Flexibility was excluded from the study because it is a capability of a manufacturing process and not an operational outcome (Swink and Hegarty, 1998). The rate of new product introduction was also not explored, as it is more dependent on research and development than on the operations organization. Further delimiting this paper, only studies providing empirical evidence of a PC→OP relationship in a manufacturing system, supply chain, or manufacturing firm were included for review. This was done to isolate the effects of PC in the absence of managerial interventions.

1.5 Trade-offs

The concept of trade-offs is key in discussions of product variety management. Authors have long claimed that it is impossible to succeed in all performance measures simultaneously (Fine and Hax, 1985; Skinner, 1974). However, others have countered this statement, showing that it is possible to achieve high levels of performance across multiple measures (Schonberger, 1986). The trade-off of offering a large product range is the need to balance the increased revenue gained from higher variety with the decreasing unit costs gained from producing or stocking lower variety (Lancaster, 1990). One of the key determinants of the PC→OP trade-off is the flexibility of process technology (Zipkin, 2001), with companies in automotive, apparel, and computer industries producing high variety (ElMaraghy et al., 2013; Holweg and Pil, 2005; Zipkin, 2001), and producers of food, textiles, paper, and oil producing less variety (Abdulmalek et al., 2006).

Other known methods for better coping with product variety and complexity include postponement (Forza et al., 2008; Scavarda et al., 2010; Swaminathan and Tayur, 1998; Um, 2017), production scheduling and sequencing (De Groote and Yücesan, 2011; Loveland et al., 2007; Swaminathan and Nitsch, 2007), product architecture, platform, and component commonality (Fisher et al., 1999; Fixson, 2005; Kim and Chhajed, 2000), product modularity (Salvador et al., 2002; Um, 2017), flexible manufacturing systems (Gupta and Goyal, 1992; Handfield and Pagell, 1995), cellular manufacturing (ElMaraghy et al., 2013; Scavarda et al., 2010; Um, 2017; Yeh and Chu, 1991), and product configurators (Trentin et al., 2012).

In examining the PC→OP relationships, this study will review the literature to see if a trade-off exists between the complexity of the assortment produced and the operational performance of the firm. While it is possible that certain OP measures may impact decisions regarding the level of PC in organizations (e.g., determining the product mix that provides the highest throughput on a given production process), this study examines only the unidirectional impact of PC on OP.

This paper is structured as follows: first, the methodology behind the systematic literature review is presented; second, the analysis and coding of the articles are described; third, emerging themes in the literature are discussed; and finally, conclusions are drawn, and future research is suggested.

2. Methodology

The systematic literature review approach proposed by Tranfield et al. (2003) was used to perform an unbiased and thorough search of the existing knowledge of the relationships between PC and OP. Systematic literature review has long been an acknowledged method for ascertaining key concepts within scholarly literature in the field of medicine, and it is becoming more widely used in the field of operations management (Burgess et al., 2006; Marasco, 2008; Seuring and Müller, 2008). In contrast with a traditional narrative literature review, systematic literature reviews are designed and reported to ensure replicability and exhaustiveness to reduce bias in the approach (Tranfield et al., 2003).
A systematic literature review typically consists of three phases: planning, conducting, and reporting (Tranfield et al., 2003). In the planning phase of this study, a search string was developed to explore the body of literature regarding the two constructs of product complexity and manufacturing performance. Two literature databases, Scopus and Web of Science (WoS), were selected because they contain relevant management and engineering journals of high academic quality and cover different sets of journals. Book chapters and conference papers were not included, as the rigor of the peer-review process cannot be guaranteed for these publications.

To ensure a comprehensive and unbiased search, the search string was developed through multiple iterations. The initial search string was constructed in collaboration with four researchers to ensure a broad perspective and reduce the risk of omitting keywords and synonyms. Keywords were added to the search string through an initial literature search until the additional terms did not yield any new results. The search strings used for each database are shown in Table 1. The search results were limited to journal articles written in English and published within the past 25 years to obtain the most recent research. The basic article data, including title, author name(s), publication name, publication year, and abstract, were extracted from the online WoS and Scopus databases and further processed in a spreadsheet.

**Table 1. Article search strings by database**

<table>
<thead>
<tr>
<th>Database</th>
<th>Search String</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scopus (Elsevier)</td>
<td>(TITLE-ABS-KEY (“product complexity” OR “product vari*” OR “product diversi*” OR</td>
</tr>
<tr>
<td></td>
<td>“product proliferation” OR “product portfolio complexity” OR “product customi*” OR</td>
</tr>
<tr>
<td></td>
<td>“product scope” OR “product hetero*” OR “product mix”) AND TITLE-ABS-KEY (“performance” OR “time” OR “speed” OR “delivery” OR “dependability” OR “quality” OR “defect” OR “scrap” OR “rework” OR “reliability” OR “flexibility” OR “productivity” OR “throughput” OR “efficiency” OR “cost” OR “inventory turn”) AND LANGUAGE (English) AND DOCTYPE (ar) AND PUBYEAR &gt; 1991 AND TITLE-ABS-KEY (“production” OR “manufactur*” OR “operation*”) AND (LIMIT-TO (SRCTYPE, “j”))</td>
</tr>
<tr>
<td>Web of Science (Thomson Reuters)</td>
<td>(TS= (“product complexity” OR “product vari*” OR “product diversi*” OR “product proliferation” OR “product portfolio complexity” OR “product customi*” OR “product scope” OR “product hetero*” OR “product mix”) AND TS= (“performance” OR “time” OR “speed” OR “delivery” OR “dependability” OR “quality” OR “defect” OR “scrap” OR “rework” OR “reliability” OR “flexibility” OR “productivity” OR “throughput” OR “efficiency” OR “cost” OR “inventory turn”) AND TS= (“production” OR “manufactur*” OR “operation*”))</td>
</tr>
</tbody>
</table>

Additional filters applied: LANGUAGE: (English) AND DOCUMENT TYPES: (Article) AND [excluding] DOCUMENT TYPES: (PROCEEDINGS PAPER), Timespan: 1992–2018

At the beginning of the review, journal quality criteria were applied to the initial sample to narrow the literature and pinpoint the most relevant and thorough studies in the field. The journals must have ranked in the first or second quartile of the Scimago Index in 2015 in operations management or a related field (e.g., engineering or strategy and management) to pass through the quality screening (Scimago Lab, 2017). Duplicate articles arising in both WOS and Scopus were also removed at this step. Next, abstract criteria were applied to the literature sample to identify articles that utilized the variables PC and OP, as listed in the search string. Only articles that discussed PC and OP as central constructs in a supply chain or manufacturing context within the abstract were assessed for full-text
reading. If it was unclear to the authors whether the abstract criteria were met for an article, the article was included for full-text reading to ensure that a reasonable sample size was reached. This screening process resulted in a sample of 284 articles.

A full-text screening was then performed to confirm that each article contained empirical evidence of the relationship between PC and one or more OP measures. To include perspectives from different methodological backgrounds, articles were selected if they had case-based evidence from a qualitative study or numerical evidence from a quantitative study supporting the existence of a PC→OP relationship. If the relationship between PC and OP was discussed without offering any empirical evidence, the article was excluded. Similarly, articles were excluded if they studied how an intervention or solution for coping with increased PC more effectively impacted an OP measure. Such articles were abundant in the sample but, if studied, would have shown the impact of the intervention on OP instead of the isolated effect of PC on OP, which was the focus of this study. The study of interventions and their effectiveness is covered in other literature reviews (ElMaraghy et al., 2013; Reis et al., 2013). With regard to quantitative research articles, only relationships between PC and OP which were statistically significant (p<0.1) were included in the analysis.

The full-text screening resulted in a final sample of 93 articles, which were then analyzed using meta-synthesis, a technique for thematically analyzing and synthesizing literature (Tranfield et al., 2003). Key variables were coded during the screening, including the PC and OP measures used, the industry and production system type of any case examples in the text, and the direction of any PC→OP relationships found in the text. Meta-analysis was not an option due to the diversity of the literature sample. The thematic synthesis and discussion were focused on the trends seen in the identified PC→OP relationships with the purpose of presenting a set of facts rather than building theory (Boer et al., 2015). Additionally, articles showing a quantitative correlation between PC and OP were interpreted as a correlation and not a causation based on the limitations of the methods.

The result of the article screening process is summarized in Figure 1, where an initial search result of 3,101 articles from both databases was reduced to 93 articles for in-depth analysis and coding. The following sections detail the reporting phase of the literature study.

![Figure 1. Article selection process](image-url)
3. Results

3.1 Publication Outlet and Trend

To understand the demographics of the final literature sample, each of the 93 articles was analyzed by publication date, publication outlet, and industry covered. Furthermore, each article was coded based on the nature of the relationships shown between the measures of PC and OP. As can be seen in Figure 2, there has been a moderate interest in the impact of PC on OP since the mid-1990s, with approximately four articles published per year on this topic and peak in publication in 2010. The results are limited to the last 25 years of research due to database restrictions and to cover the most recent research in the area.

Journals publishing studies on the operational impact of PC came from the domains of business strategy and management, operations management, operations research, engineering, and economics. An overview of the journals appearing most frequently in the final article set is shown in Table 2. The six publications in Table 2 reside in the operations management and operations research domains, which is logical since the impact of complexity on product and business processes has been a primary concern of top management in recent decades (KPMG, 2011). Apart from the journals in Table 2, approximately 37 other journals were represented in the final article set, with each journal having one or two articles in the sample.

![Figure 2. Published articles discussing the relationships between PC and OP, showing the absolute number of articles per year and the cumulative number of articles per year](image)
Table 2. Top publications in the literature search with more than two articles in the final article set

<table>
<thead>
<tr>
<th>Publication Name</th>
<th>Number of Articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>International Journal of Production Research</td>
<td>13</td>
</tr>
<tr>
<td>International Journal of Production Economics</td>
<td>9</td>
</tr>
<tr>
<td>International Journal of Operations and Production Management</td>
<td>8</td>
</tr>
<tr>
<td>Management Science</td>
<td>7</td>
</tr>
<tr>
<td>Production and Operations Management</td>
<td>6</td>
</tr>
<tr>
<td>Journal of Operations Management</td>
<td>6</td>
</tr>
</tbody>
</table>

3.2 Industry Considered

The research detailing the PC→OP relationship spans a range of industries, as can be seen in Table 3. To classify the industries of the cases and examples used in the articles, the Standard Industrial Classification (SIC) scheme was applied (OSHA, 2017). The articles that used cases or examples to illustrate their purposes were classified using two-digit industry codes. Three-digit codes were not available for the entire set of articles, so the two-digit codes were analyzed instead. Articles with four or fewer cases companies appear multiple times in Table 3, with each case company counting as one instance. Articles with five or more companies in the assessed literature sample are counted in the code “Mixed.” Articles with no distinct industry group, such as a model of a general flexible manufacturing system, are counted in the group “N/A.” To provide a view on the nature of the manufacturing process in each article, the authors categorized the SIC codes as using primarily job shop, batch production, assembly line, manufacturing cells, or continuous flow systems based on the manufacturing system classification of Hayes and Wheelwright (1979).

The results of the industry analysis show a heavy representation of automotive manufacturers, followed by electronics, machinery, and food and beverage manufacturers. Underrepresented in the list are case companies operating with continuous flow processes in process industries, with a minor representation in the food and beverage industry (three cases) along with two chemicals cases, one glass case, and one primary metals case. Process industries typically reside upstream of the supply chain and employ less flexible equipment than assembly systems relying on manual labor (Abdulmalek et al., 2006; Fransoo, 1992).

3.3 Measures of PC

Examining the literature for insights into the PC→OP relationship revealed a range of operationalization for PC measures (see Table 4). The measures used in the literature sample can be organized in five categories: structural PC measures related to product architecture, composite PC measures created with multiple structural PC measures or survey responses, demand distribution measures, production measures, and the degree of product customization. Product variety, measured in terms of the number of end items, or stock keeping units (SKUs), was used most frequently, followed by the number of components. Some variations of PC measures incorporated individual product features specific to the analyzed production system, such as model mix and parts complexity for automotive production. Many of the PC measures are detailed variety measures, whereas fewer address the interrelatedness of the components to make it a true complexity indicator (Jacobs, 2013). One economics paper measures PC using the Herfindahl index, which captures the distribution of the demand for a set of products or product segments (Gollop, 1997). Herfindahl indices contain more information in a single value but are less understandable from an operational perspective when examining production systems.
A study by Hu et al. (2008) on product variety-induced manufacturing complexity was added to Table 4 as a measure of PC, although it does not appear in the final article set. This was done because the study presents a concept critical to the discussion of the impact of PC on performance in assembly processes.

Table 3. Article case examples grouped by industry code

<table>
<thead>
<tr>
<th>SIC Code (two-digit)</th>
<th>Production System</th>
<th>Number of Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>37 Transport equipment (cars, motorcycles, bicycles)</td>
<td>Assembly line</td>
<td>21</td>
</tr>
<tr>
<td>36 Electronics (circuit boards)</td>
<td>Assembly line</td>
<td>10</td>
</tr>
<tr>
<td>20 Food and beverage</td>
<td>Continuous &amp; batch</td>
<td>9</td>
</tr>
<tr>
<td>23 Apparel</td>
<td>Batch production</td>
<td>3</td>
</tr>
<tr>
<td>35 Machinery and equipment (computers, hard drives)</td>
<td>Assembly line</td>
<td>3</td>
</tr>
<tr>
<td>28 Chemicals and allied products</td>
<td>Continuous &amp; batch</td>
<td>2</td>
</tr>
<tr>
<td>31 Leather Products (Footwear)</td>
<td>Batch production</td>
<td>2</td>
</tr>
<tr>
<td>34 Fabricated Metal Products</td>
<td>Manufacturing cells</td>
<td>2</td>
</tr>
<tr>
<td>22 Textile mill products</td>
<td>Batch production</td>
<td>1</td>
</tr>
<tr>
<td>32 Stone, clay, glass (flat glass)</td>
<td>Continuous</td>
<td>1</td>
</tr>
<tr>
<td>33 Primary metals (rolled steel)</td>
<td>Continuous</td>
<td>1</td>
</tr>
<tr>
<td>39 Miscellaneous (hairbrush producer)</td>
<td>Batch production</td>
<td>1</td>
</tr>
<tr>
<td>47 Transportation services</td>
<td>N/A</td>
<td>1</td>
</tr>
<tr>
<td>50 Trade-durable goods (medical devices)</td>
<td>Assembly line</td>
<td>1</td>
</tr>
<tr>
<td>59 Miscellaneous retail (sporting goods)</td>
<td>Assembly line</td>
<td>1</td>
</tr>
<tr>
<td>Mixed</td>
<td>N/A</td>
<td>18</td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>22</td>
</tr>
</tbody>
</table>

*Note: an article may appear more than once in this list, therefore the sum > 94 articles.*

3.4 Measures of OP

The measures of OP identified in the literature sample were highly fragmented, with over 42 different measures for time, cost, quality, and delivery performance. Due to length restrictions, the final table of OP measures is presented in the Appendix. The OP measures are discussed in the analysis section.
Table 4. Product complexity (PC) measures identified in the literature sample

<table>
<thead>
<tr>
<th>PC Measure</th>
<th>Definition</th>
<th>Publication</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural PC measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product variants</td>
<td>The number of finished variants in the production system and/or offered to the customer, SKU count in a warehouse or distribution center, or product line depth, also referred to as external variety</td>
<td>(Abbey et al., 2013; Abernathy et al., 2000; Ahmad and Shroeder, 2001; Alford et al., 2000; Alvarez et al., 2016; Anderson, 1995; Appelqvist et al., 2013; Benjaafar et al., 2004; Berman, 2011; Berry and Cooper, 1999; Bozarth et al., 2009; Brabazon et al., 2010; Celano et al., 2012; Cusumano, 1994; Deane and Yang, 1992; Djassemi, 2005; Engström et al., 1995; Erens and Hegge, 1994; Gupta and Srinivasan, 1998; Gupta and Goyal, 1992; Holweg, 2005; Lanza et al., 2010; Maps et al., 1997; O’Reilly et al., 2015; Pil and Holweg, 2004; Rajagopalan and Swaminathan, 2001; Scavarda et al., 2010; Silvera, 1998; Thonemann and Bradley, 2002; Wan et al., 2012, 2014; Wan and Dressner, 2015; Wan and Sanders, 2017; Ward et al., 2010; Zhang et al., 2007)</td>
<td>35</td>
</tr>
<tr>
<td>Components</td>
<td>The number of components or the number of options for a specific component (e.g., layers on a computer chip, options for auxiliary parts, number of component configurations, packaging type)</td>
<td>(Bozarth et al., 2009; Brin and Pero, 2012; Closs et al., 2010, Er and MacCarthy, 2006; Escobar-Saldívar et al., 2008; Holweg, 2005; Hirsch and Tong, 2006; Huang and Inman, 2010; Inman and Blumenfeld, 2014; Kadakia et al., 1994; Keil et al., 2014; Roy et al., 2011; Sardar and Lee, 2015; Shah et al., 2017; Zhang and Tseng, 2007)</td>
<td>15</td>
</tr>
<tr>
<td>Product families</td>
<td>The number of product families or product lines (e.g., car makes and models)</td>
<td>(Moreno and Terwiesch, 2017; Nandkeolyar and Chrysti, 1992; Sardar and Lee, 2015; Shah et al., 2017; Wong and Eayers, 2011; Zhang and Tseng, 2007)</td>
<td>6</td>
</tr>
<tr>
<td>Product platforms</td>
<td>The number of product platforms</td>
<td>(Van Den Broeke et al., 2015)</td>
<td>1</td>
</tr>
<tr>
<td>Commonality</td>
<td>The number of similar parts</td>
<td>(Nagarur and Azzeen, 1999)</td>
<td>1</td>
</tr>
<tr>
<td>Variety (ranking)</td>
<td>Product variety, measured as minimal, low, medium, or high with a survey question</td>
<td>(Koh et al., 2005)</td>
<td>1</td>
</tr>
<tr>
<td>Complexity (ranking)</td>
<td>Ranking of 0 to 1 based on the complexity of interacting components</td>
<td>(Novak and Eppinger, 2001)</td>
<td>1</td>
</tr>
<tr>
<td>Complexity (perceived)</td>
<td>Perceived complexity of the product</td>
<td>(Maruthi and Roshan Joseph, 1999)</td>
<td>1</td>
</tr>
<tr>
<td><strong>Composite PC measures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product complexity (survey measure)</td>
<td>Varies but aggregates measures of the number of product families, the number of components, customization of products, average parts per BOM, the degree of modularity, the ability to add new products, etc.</td>
<td>(Blome et al., 2014; Caniato and Größler, 2015; Christensen et al., 2007; Eckstein et al., 2015; Hegde et al., 2005; Helkio and Tenhialä, 2013; Koh et al., 2005; Thomé, Sousa and Scavarda do Carmo, 2014; Tracey, 2004)</td>
<td>9</td>
</tr>
<tr>
<td>Product complexity (composite)</td>
<td>Composite measure of the number of attributes, number of variants, weighted by manufacturing cost, the relative demand of a product, etc.</td>
<td>(Anderson, 1995; Ding et al., 2007; Sun and Ding, 2010; Vilas and Vandaele, 2002)</td>
<td>4</td>
</tr>
<tr>
<td>Model mix complexity</td>
<td>Function of the number of car models, body types, models; also corrects for the number of assembly lines per plant</td>
<td>(Ittner and MacDuffie, 1995; MacDuffie et al., 1996)</td>
<td>2</td>
</tr>
<tr>
<td>Parts complexity</td>
<td>Function of the number of engine transmissions, wire harnesses, exterior paint colors, suppliers, parts in assembly, and percentage of common parts</td>
<td>(Ittner and MacDuffie, 1995; MacDuffie et al., 1996)</td>
<td>2</td>
</tr>
<tr>
<td>Options variability</td>
<td>Standard deviation in the number of options per car for 8 key options</td>
<td>(Fisher and Ittner, 1999; MacDuffie et al., 1996)</td>
<td>2</td>
</tr>
<tr>
<td>Options content</td>
<td>Average number of options per car in each month</td>
<td>(Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996)</td>
<td>3</td>
</tr>
<tr>
<td><strong>Demand distribution</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product mix skewness</td>
<td>The distribution of demand across products, where low skewness represents equally distributed demand across products and extreme skewness represents demand concentrated on a few variants</td>
<td>(Akkerman and van Donk, 2007; Jensen et al., 1996; Ruiz-Torres and Mahmoodi, 2007, 2008, Seifoddini and Djassemi, 1996, 1997)</td>
<td>6</td>
</tr>
<tr>
<td>Herfindahl type</td>
<td>[ d = 1 - \sum_{i=1}^{k} s_i^2 + \sum_{i=1}^{k} \sum_{j=1}^{k} s_i s_j f_{ij}, ] where ( s_i ) is the share of sales from product ( i ) and ( k ), and ( f_{ij} ) is a distance function between products ( i ) and ( k ), or similar variation</td>
<td>(Aw and Lee, 2009; Brahm et al., 2017; Gollop, 1997; Vachon and Klassen, 2002)</td>
<td>4</td>
</tr>
<tr>
<td>Entropy index</td>
<td>[ \sum_{p=1}^{m} s_p \ln(s_p), ] where ( s_p ) is the share of sales for product ( p )</td>
<td>(Baldwin et al., 2012; Thirumalai and Sinha, 2011)</td>
<td>2</td>
</tr>
<tr>
<td>Demand interrelatedness</td>
<td>Correlation of the demand between products and packaging type</td>
<td>(Akkerman and van Donk, 2009)</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4. Product complexity (PC) measures identified in the literature sample (continued)

<table>
<thead>
<tr>
<th>PC Measure</th>
<th>Definition</th>
<th>Publication</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Batch size</td>
<td>Production run length used as an indicator of variety</td>
<td>(Berry and Cooper, 1999; Celano et al., 2012; Nazarian et al., 2010)</td>
<td>3</td>
</tr>
<tr>
<td>Setups</td>
<td>The number of setups as an indicator of variety</td>
<td>(Anderson and Sedatole, 2012; Yang and Deane, 1993)</td>
<td>2</td>
</tr>
<tr>
<td>Product variety-induced manufacturing complexity</td>
<td>Measures of the information entropy at a workstation due to the choice of components, tools, work procedures, etc.</td>
<td>(Busogi et al., 2017; Hu et al., 2008)</td>
<td>2</td>
</tr>
</tbody>
</table>

Degree of customization

<table>
<thead>
<tr>
<th>OP Measure</th>
<th>Positive relationship</th>
<th>No relationship</th>
<th>Negative relationship</th>
<th>U-shape</th>
<th>Inverted U-shape</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Costs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operations costs (general)</td>
<td>1</td>
<td>4</td>
<td>16</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Direct labor costs</td>
<td>1</td>
<td>5</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufacturing overhead costs</td>
<td></td>
<td></td>
<td>4</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inventory costs</td>
<td>1</td>
<td>2</td>
<td>12</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lead time</td>
<td>1</td>
<td>4</td>
<td>14</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processing time</td>
<td>1</td>
<td>3</td>
<td>14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Setup time</td>
<td></td>
<td></td>
<td>10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Productivity</td>
<td></td>
<td></td>
<td>1</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quality</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delivery</td>
<td>2</td>
<td>9</td>
<td>11</td>
<td>2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.5 Analysis of PC→OP Relationships

Every relationship between PC and OP identified through the full-text literature review and coding was mapped, with the collective work summarized in Table 5. The relationships received a primary code based on the detailed OP measure used and a secondary code based on the direction of the relationship: positive, no relationship, negative, U-shape, inverted U-shape, and other relationship. Positive relationships between PC and OP were defined as being beneficial for business performance, meaning increasing time-based performance (e.g., increased throughput or efficiency, decreased cycle time, decreased lead time), decreasing cost, increasing quality or decreasing rework, and increasing delivery reliability. Negative relationships imply a detrimental relationship between PC and OP. The category “no relationship” was included to categorize the articles that tested relationships but reported them as non-significant. Examples supporting the PC→OP relationships shown in Table 5 are discussed below.

Table 5. Relationships identified in full-text readings between product complexity (PC) and operational performance (OP) measures
3.6 PC is related to increasing operations and inventory costs, but no impact on labor

3.6.1 General manufacturing costs. There are numerous articles supporting the claim that increased PC leads to increased manufacturing and supply chain costs (Alford et al., 2000; Berman, 2011; Bozarth et al., 2009; Ding et al., 2007; Lanza et al., 2010; Mapes et al., 1997; Moreno and Terwiesch, 2017; Roy et al., 2011; Sardar and Lee, 2015; Silveira, 1998; Squire et al., 2006; Sun and Ding, 2010; Thonemann and Bradley, 2002; Wan and Dresner, 2015; Wong and Eyers, 2011; Zhang and Tseng, 2007). Most of these studies suggest a linear relationship between the number of finished products or product families produced and operations costs.

Two articles identified an inverted U-shaped relationship between PC and operations costs (Wan, 2016; Wan and Dresner, 2015), meaning that increasing PC becomes less costly the more PC a firm produces, up until the point that costs decrease with added PC. Both studies identifying this relationship were performed in soft-drink bottling facilities, with one study examining a measure of pack size variety (Wan, 2016) and the other examining the total SKUs produced (Wan and Dresner, 2015). One explanation for the inverted U-shaped relationship is that variety can be added in a way that has minimal impact on the production system. For example, a soft-drink company with a standard pack size of 12 units adding a new packing variant of 24 units would incur less additional operations and logistics costs than if they were to add a new packing variant of 30 units, presuming that the packaging of the 12- and 24-unit variants was similar (Wan, 2016). The author argued that “with higher pack-size variety, different packs are more likely to have similar shapes and size,” thus, supporting a concave curvilinear relationship (Wan, 2016, p. 273).

In contrast, a U-shaped relationship was identified by Van Den Broeke et al. (2015), who studied the relationship between the number of product platforms and total supply chain costs, showing that too few platforms lead to high customization costs to make the end products unique, while too many platforms (e.g., one platform per product line) lead to a higher purchasing price for the platform due to the lower quantity ordered.

Four survey studies identified no relationship between operations costs and the number of components, degree of product customization, and composite measures of product complexity (Bortolotti et al., 2013; Bozarth et al., 2009; Caniato and Größler, 2015; Helkiö and Tenhiälä, 2013).

Only one study found that higher PC led to lower manufacturing costs (Eckstein et al., 2015). Eckstein et al. (2015) measured PC as an aggregated result of responses to survey questions about the number of product components, number of new variants, customization degree, and value-added services. Cost performance was a survey measure based on the costs of manufacturing, inventory, transportation, handling, and purchased goods. This direct effect was found when building a preliminary model to test the moderating effect of product complexity on the effect of supply chain adaptability on cost performance (Eckstein et al., 2015). However, the authors did not explain the reason for the positive impact of PC on cost performance in the preliminary model.

3.6.2 Direct labor. In assessing the impact of PC on direct labor, the results are mixed across three automotive studies (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996). Since many PC measures are used, each having unique impacts on direct labor costs, a summary of the relationships is presented in Table 6. The studies show that parts complexity consistently increases direct labor costs (negative relationship) while model mix complexity does not impact direct labor hours. Measures of options complexity and variability show mixed results. Possible reasons for the lack of a relationship between model mix and options-related PC measures are the placement of slack labor at workstations with high PV (Fisher and Ittner, 1999), the presence of lean capabilities (MacDuffie et al., 1996), production line design for mixed model assembly.
(MacDuffie et al., 1996), and options bundling (Ittner and MacDuffie, 1995). The counter-intuitive finding that options variability decreases direct labor costs was particularly surprising to the study’s authors, who suggest that the correlation could be linked to the capability of the analyzed manufacturing plants to handle a high product mix (MacDuffie et al., 1996).

Table 6. Impact of specific PC measures on direct labor costs (grey indicates N/A)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Model mix complexity</td>
<td>no rel</td>
<td>no rel</td>
<td></td>
</tr>
<tr>
<td>Parts complexity</td>
<td>–</td>
<td>–</td>
<td></td>
</tr>
<tr>
<td>Options content/complexity</td>
<td>no rel</td>
<td>–</td>
<td>no rel</td>
</tr>
<tr>
<td>Options variability</td>
<td>+</td>
<td>+</td>
<td>no rel</td>
</tr>
</tbody>
</table>

3.6.3 Manufacturing overhead costs. The relationships between PC and measures of manufacturing overhead (MOH) costs, such as indirect labor and fixed manufacturing expenses, are summarized in Table 7. Articles finding an increase in MOH costs with increased PC (negative relationship in this study) were focused on automotive firms (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; Scavarda et al., 2010), household appliance firms (Brun and Pero, 2012), textile manufacturers (Anderson, 1995), and a float glass manufacturer (Anderson and Sedatole, 2012). In a study of three textile plants, only three of seven attributes were found to be negatively related with MOH, with different variety measures being statistically significant in each plant, while the other four had no relationship with MOH (1995). According to the author, “this research demonstrates that, at least in some environments, attribute-based measures of [product complexity] achieve their objective of providing improved estimation and greater understanding of [MOH] and its drivers” (Anderson, 1995, p. 382). One of the key findings of these articles is that specific PC measures significantly impact MOH in each industry and factory context, making it difficult to generalize the PC→MOH relationship across studies.

One set of authors elucidated the PC→MOH relationship with a few key sentences, stating, “With an increasingly complex product mix comes additional parts, greater inventory and material handling, additional setups, more complex scheduling and task assignment, and increased supervisory requirements” (Ittner and MacDuffie, 1995, p. 315), with the mentioned effects falling under MOH costs. Another perspective is given by Scavarda et al. (2010), who found that PC offered to the market can create more MOH in emerging markets due to the need for increased training time (Scavarda et al., 2010). This reveals the importance of the country context and market maturity when assessing the PC→OP relationship.
Table 7. Impact of specific PC measures on manufacturing overhead costs (grey indicates N/A)

<table>
<thead>
<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of variants</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Component options</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Model mix complexity</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Parts complexity</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Options content/complexity</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Options variability</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Number of setups</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
<tr>
<td>Textile factors</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>no rel</td>
<td>(3 of 7)</td>
</tr>
</tbody>
</table>

Four studies in the literature set found no relationship between specific measures of product variety and MOH. In the automotive sector, the complexity of main models had no relation to MOH because model variety primarily affects the body shop and not the final assembly stage of car manufacturing (Ittner and MacDuffie, 1995). The options content (or number of options) per car on a production line showed no significant relationship with MOH; it was the variation in options content created by both demand variation and production scheduling that proved to have a greater effect on operations, complicating production scheduling (Fisher and Ittner, 1999). The third study of a float glass manufacturer found that the number of setups (a proxy measure of product variety) has no relationship with monthly MOH, which the authors attributed to the high level of automation minimizing the need for surplus manning during changeovers (Anderson and Sedatole, 2012).

3.6.4 Inventory Costs. The impact of PC on inventory costs was found to be detrimental in eleven cases within the literature sample, where inventory costs increase as PC increases (Abbey et al., 2013; Abernathy et al., 2000; Benjaafar et al., 2004; Escobar-Saldívar et al., 2008; Fisher and Ittner, 1999; Moreno and Terwiesch, 2017; O’Reilly et al., 2015; Pil and Holweg, 2004; Rajagopalan and Swaminathan, 2001; Seifoddini and Djassemi, 1996; Wan and Sanders, 2017; Ward et al., 2010). The predominant PC measure used in the inventory literature was the number of products in the system or in the product line. Many companies keep stock of each finished product variant to improve lead times and service levels for the customer. Thus, if the number of product variants increases, it is logical to assume that inventory levels and cost will also increase. This relationship has been found to be largely linear (Benjaafar et al., 2004; Moreno and Terwiesch, 2017; Wan and Sanders, 2017), although there is evidence of a U-shaped relationship between PC and inventory costs (Brabazon et al., 2010).

Other factors affecting the PC→inventory cost relationship identified in the literature are the stocking strategy and forecast bias. First, Pil and Holweg (2004) explained that if a company builds to stock or builds to forecast, more variants will be held in inventory, and inventory costs will rise. However, if a firm builds to order and keeps no finished stock, the relationship of PC with inventory costs will not be negative unless the firm needs to keep a significantly higher number of components and work in process inventory. Second, Wan and Sanders (2017) showed that the
number of SKUs affected inventory levels through forecast bias in a distribution center for beverages. Furthermore, they demonstrated that vertical integration of the supply chain lessens the impact of PC on inventory levels.

Two instances emerged where PC had no relationship with inventory costs in automotive plants (Appelqvist et al., 2013; Fisher and Ittner, 1999). The lack of a relationship between options content and inventory costs was not explained by Fisher and Ittner (1999). However, in a case study of decreasing product variants in a sporting goods manufacturer, Appelqvist et al. (2017) found that many of the products that were removed were not being sold, and therefore the reduction did not affect inventory levels. The single article finding a positive relationship between the number of car makes and inventory costs was that of Moreno and Terwiesch (2017), although the coefficient was not very large and the authors did not offer a causal explanation.

3.7 PC is related to increasing lead time, processing time, setup time, and decreasing productivity

3.7.1 Lead time. Product complexity was related to increasing lead time (negative relationship with respect to performance) in fourteen examples within the literature sample (Akinc and Meredith, 2015; Akkerman and van Donk, 2009; Berman, 2011; Feng et al., 2011; Holweg, 2005; Inman and Blumenfeld, 2014; Mapes et al., 1997; Squire et al., 2006; Thonemann and Bradley, 2002; Vilas and Vandaele, 2002; Ward et al., 2010; Wong and Lesmono, 2013; Xia and Rajagopalan, 2009; Zhang et al., 2007). The negative PC \(\rightarrow\) lead time relationships identified in the literature sample were linear (Mapes et al., 1997; Zhang et al., 2007), concave, and increasing as an exponential function (Thonemann and Bradley, 2002). Two U-shaped relationships were found in a simulation study of the number of product variants of an automobile manufacturer (Brabazon et al., 2010) and in a study on the product mix skewness of a food producer (Akkerman and van Donk, 2007).

Zhang and Chen (2007) provided evidence for both a “negative relationship” and a “no relationship” classification (Table 5), where an increasing number of base models in an automotive factory is related to increasing lead time, while the average number of car types per model (e.g., body, engine) is not related to lead time. Three other articles identified no relationship between PC and lead time (Caniato and Größler, 2015; Christensen et al., 2007; Vachon and Klassen, 2002), all of which involved large sample populations and utilized survey-based measures of PC and lead time.

One study in the literature sample identified a positive relationship between PC and lead time (Gupta and Srinivasan, 1998). Applying queuing theory and using order backlog as a proxy measure for lead time, Gupta and Srinivasan (1998) demonstrated that total backlog can decrease with increasing product variants if the production rates are adjusted across the products and the utilization of the factory is kept constant. Furthermore, the authors stated that if factory utilization increases with increasing PC and no processing time adjustments are made to stabilize factory utilization, it is likely that the backlog and lead time will increase. This relationship was coded as positive because the management interventions of adjusting production rates and utilization were seen to fall within daily operations management activities and not as extreme changes in production strategy (e.g., investing in flexible technology, reconfiguring the supply chain).

Increasing the number of product variants in operations can cause complexity in production, increase the likelihood of errors due to an increased number of transactions, increase the risk of a disruption to the supply chain (e.g., a supplier’s failure to deliver critical components), create unplanned delays, and increase the overall lead time to the customer (Inman and Blumenfeld, 2014; Jacobs and Swink, 2011; Mapes et al., 1997). It was also found that increased lead times could be due to increased order processing time but not increased manufacturing processing time (Zhang et al., 2007).
Variability in demand resulting from high product variety was also shown to be a key factor in the PC→lead time relationship. Vilas and Vandaele (2002) found that lead time increased as the variety within a manufacturing system became more differentiated or skewed in production times, setup times, and batch sizes such that one product form was notably higher in these dimensions than the others. Increased demand correlation between products was shown to increase lead times in a food processing company because of the resulting imbalance in the production system, which increased the machine blockage and starvation times (Akkerman and van Donk, 2009).

A further moderating factor mentioned in the literature was the choice of the customer order decoupling point. Two papers argued that the choice of the customer order decoupling point also affects lead time when comparing firms; for example, an engineer-to-order firm will have longer lead times than an assemble-to-order firm (Akinc and Meredith, 2015; Holweg, 2005). Product customization will automatically create a longer lead time than standard products due to the extra time needed to design or configure the product, as can be seen in the lead times for custom Levi’s blue jeans and other garments (Xia and Rajagopalan, 2009).

3.7.2 Processing time. Assessing the impact of PC on processing time in various manufacturing contexts led to mixed results, with fourteen articles finding evidence of a negative relationship (increasing processing time, queuing time, job waiting time, machine flow time, order tardiness, etc.) (Busogi et al., 2017; Djassemi, 2005; Engström et al., 1995; Er and MacCarthy, 2006; Gupta and Goyal, 1992; Jensen et al., 1996; Keil et al., 2014; Nagarur and Azeem, 1999; Nazarian et al., 2010; Ruiz-Torres and Mahmoodi, 2008, 2007, Seifoddini and Djassemi, 1996, 1997; Yang and Deane, 1993), three articles finding evidence of no relationship (Er and MacCarthy, 2006; Vachon and Klassen, 2002; Zhang et al., 2007), and one article finding a positive relationship (Ruiz-Torres and Mahmoodi, 2007). The one instance of a positive PC→processing time relationship occurred for a flexible manufacturing shop where cells designed to produce more product families had an improved processing time with a more extreme product mix (Ruiz-Torres and Mahmoodi, 2007).

A few of the factors moderating the PC→processing time relationship are the flexibility of the manufacturing system, the skill level of the workforce, and the criticality of components being diversified. Regarding machine flexibility, product mix variability was shown to have a greater impact on cell shops than on job shops, which are known for their flexibility (Jensen et al., 1996). Similarly, factories with dedicated manufacturing cells designed to produce one product family had increased processing times under a more extreme product mix (Ruiz-Torres and Mahmoodi, 2007). Regarding skill level, adding cross-functional workforce reduced the effect of added variety in both cellular manufacturing and job shops (Djassemi, 2005). Er and MacCarthy (2006) appear in both the “negative relationship” and “no relationship” categories, as they found that individual types of variety in manufacturing influence processing time differently. As the number of critical materials in an upstream manufacturing process increases from 1 to 5, the flow time increases 29% due to the additional setups and material shortages, which cause production to stop. Contrastingly, the authors found that downstream variety in terms of the amount of packaging materials was not related to processing time, as the packaging materials were not as critical.

One of the most discussed mediation variables between PC and OP is product variety-induced manufacturing complexity (PVIMC), or the information entropy provided to an operator at a workstation that affects his or her choice of components, tools, fixtures, and work procedures (Hu et al., 2008; Zeltzer et al., 2013). While six articles discussing PVIMC appeared in the full-text screening phase of the literature study, only one of these articles included empirical evidence for the relationship between PVIMC and OP. Busogi et al. (2017) demonstrated that having many similar yet unique components in a workstation increases the choice complexity and the reaction time needed to distinguish between components and select the appropriate one.
3.7.3 Setup Time. While it is possible to logically deduce the impact of PC on setup times (greater variety produced in the same amount of time increases product changeovers), ten articles in the final literature set contained empirical evidence of this in apparel, chemicals, household appliance, sheet metal, automobile, street scooter, and generic manufacturing systems as well as in mass manufacturing surveys (Anderson, 1995; Baldwin et al., 2012; Berry and Cooper, 1999; Brun and Pero, 2012; Celano et al., 2012; Cusumano, 1994; Escobar-Saldívar et al., 2008; Kampker et al., 2012; Sardar and Lee, 2015; Vilas and Vandaele, 2002). No articles were found suggesting a positive relationship (decreasing setup time) or an absence of a relationship between the variables in question.

3.7.4 Productivity. Product variety led to decreased process productivity in every article that studied the PC→productivity relationship (Anderson and Sedatole, 2012; Aw and Lee, 2009; Berry and Cooper, 1999; Gollop, 1997; Nagarur and Azeem, 1999; Nandkeolyar and Christy, 1992; Silveira, 1998). Decreased productivity due to PC occurs due to the reduced line speeds, increased downtime, and increased number of process adjustments that come with producing a higher variety of products, especially on process lines (Berry and Cooper, 1999). However, more flexible processes do not experience the same loss in productivity with increasing variety (Nandkeolyar and Christy, 1992). A further contingency variable related to the effect of PC on process productivity is the sequencing of production orders, where short orders planned in an optimal sequence show no negative impact on process productivity (Berry and Cooper, 1999).

One study showing a lack of relationship between PC and productivity looked at the effect of adding, dropping, or maintaining products on the total factor productivity of 3330 Chilean manufacturing plants. Companies that only added products showed no statistically significant changes in total factor productivity, but firms that added new products and dropped products in the same year increased total factor productivity compared to companies that did not change product variety or only added or dropped products (Alvarez et al., 2016). This study gives weight to the portfolio review process and the “one-in, one-out” rule for managing product portfolios.

An inverted U-shaped relationship was identified between PC (Herfindahl type index) and productivity (i.e., the natural logarithm of average drop size) in a transportation company (Brahm et al., 2017). One of the mechanisms at play in the study was operational friction, which is created by adding a variety that is dissimilar from the variety currently being offered (e.g., adding a confectionary product line when the company mostly produces beverages). This friction takes the form of modified work routines, increased communication, and a need to manage interdependencies in the business, all of which can erode productivity. However, the authors found evidence that these operational frictions could be reduced with more worker experience (Brahm et al., 2017).

3.8 PC → Unclear effect on quality performance

The literature investigating the impact of PC on quality measures, such as the rework percentage, repair costs, error rate, and inspection costs, was equally distributed between the “no relationship” and “negative relationship” classifications. Articles finding a negative relationship between PC and quality measures assessed the impact of detailed variety measures, such as options variability, plant build complexity, the number of component options, run length, and the degree of customization (Berman, 2011; Brun and Pero, 2012; Celano et al., 2012; Fisher and Ittner, 1999; Hegde et al., 2005; Huang and Inman, 2010; Mapes et al., 1997; Maruthi and Roshan Joseph, 1999; Novak and Eppinger, 2001; Shah et al., 2017; Silveira, 1998; Thirumalai and Sinha, 2011). The line of reasoning for the negative PC→quality relationship is that a higher number of products impedes operational focus, resulting in manufacturing errors, order mismatches, and rework (Shah et al.,
In process industries, increased variety leads to small batches, which result in increased inspection costs due to the inability to adequately determine a steady-state mean and standard deviation for the process (Celano et al., 2012). Novak and Eppinger (2001) found that the negative PC→quality relationship is moderated by the make/buy decisions of the firm. Further, they provided case evidence suggesting that companies that outsource complex components receive lower quality components than those that make the more complex components in-house.

Articles that found no PC→quality relationship mostly employed composite PC measures (e.g., options content, model mix, and survey PC measures) (Caniato and Größler, 2015; Fisher and Ittner, 1999; Helkiö and Tenhialä, 2013; MacDuffie et al., 1996; Mapes et al., 1997; Shah et al., 2017; Squire et al., 2006; Thomé, Sousa and Scavarda do Carmo, 2014). One explanation that was given for the lack of a PC→quality relationship was the impact of relentless focus on improving quality for manufacturers in OECD countries in the 1980s (Squire et al., 2006).

The degree of customization PC measure was a subject of disagreement in the literature sample. Squires et al. (2006) found no relationship between customization and quality, while Hegde et al. (2005) found support for both a negative, linear relationship and an inverted U-shaped relationship. Looking closer at the studies, Hegde et al. (2005) performed a regression analysis of 322 iron and steel foundries, whereas Squire et al. (2006) used an analysis of variance methods to examine 102 UK manufacturing industries, with a specific focus on firms affected by mass customisation. The exact reason for the differing results is unknown, but it could be related to the difference in the industry domains and the methods of operationalizing PC and quality variables in their large data sets.

Two articles in the sample did not fit into a classification in Table 5, as they developed specific mathematical relationships to predict the yield of an integrated circuit (IC) board and multi-chip module process based on specific product features, such as the product surface area and number of layers (Hsieh and Tong, 2006; Kadakia et al., 1994). These are two of three articles in the literature sample discussing the impact of PC on yield for IC manufacturers.

3.9 PC → Unclear effect on delivery performance

The discussion surrounding the relationship between PC and measures of delivery performance was roughly equally split between “no relationship” and “negative relationship,” with a few exceptions. Articles categorized as showing a negative relationship included assessments of unit and order fill rates (Closs et al., 2010; Mapes et al., 1997; Wan et al., 2012, 2014) and delivery reliability and responsiveness (Ahmad and Shroeder, 2001; Appelqvist et al., 2013; Jensen et al., 1996; Koh et al., 2005; Mapes et al., 1997; Rosenzweig, 2009; Ruiz-Torres and Mahmoodi, 2008). A few of these cases were linear in nature (Ahmad and Shroeder, 2001; Appelqvist et al., 2013; Closs et al., 2010; Wan et al., 2014). Increasing PC in manufacturing and supply chains can increase the uncertainty in product demand (Koh et al., 2005) as well as in the number of decisions made by a company towards suppliers, customers, and competitors, increasing the time needed to coordinate activities (Ahmad and Shroeder, 2001) and the likelihood of errors in the value chain, including delivery errors (Mapes et al., 1997).

Two cases of a U-shaped relationship between PC and delivery performance were identified in a study examining the number of products of a beverage distributor (Wan et al., 2012, 2014). Wan, Evers, and Dresner (2012) modeled the relationship between SKUs and fill rate as a convex and decreasing U-shape with the inflection point, or threshold product variety level, being outside of the feasible range. The authors tested this relationship with the idea that adding variety at low variety levels, when products tend to have greater dissimilarity, hinders delivery performance more than at high levels of variety, when products are more similar to each other (Wan et al., 2012). The number of products per line had a U-shaped relationship with the order fill rate (Wan et al., 2014). This
relationship likely results from difficulties in forecasting demand and managing inventory at distribution centers. One explanation for this marginal effect is that high similarities exist between new products and existing products when product line variety is already high, which could reduce the negative operational impact.

Articles classified as having no PC→delivery performance relationship mostly utilized composite PC measures based on survey results and the degree of product customization (Ahmad and Shroeder, 2001; Appelqvist et al., 2013; Bortolotti et al., 2013; Caniato and Größler, 2015; Eckstein et al., 2015; Helkiö and Tenhiälä, 2013; Koh et al., 2005; Squire et al., 2006; Thomé, Sousa and do Carmo, 2014; Vachon and Klassen, 2002). One of the explanations for the lack of a relationship between product customization and delivery performance is that many firms offering a high variety of products employ methods such as variety reduction, modularity, and mass customization, which can moderate the negative effects of product customization (Bortolotti et al., 2013), thus making the effect of high PC less visible.

As for the two positive PC→delivery relationships, PC led to higher outbound transport effectiveness and delivery service in a survey of 180 manufacturing firms (Tracey, 2004) and decreased backlog in a make-to-order manufacturing system (Gupta and Srinivasan, 1998). The authors of the first article did not explain their results, while the results of the second study are partially due to the regulation of product demand as variety increases.

4. Discussion

Based on the literature coding and analysis, it can be concluded that the overarching relationship between PC and OP is negative. The literature coding and analysis summarized in Table 5 revealed that cost and time OP measures were studied more frequently than quality and delivery measures. The negative impact of PC on general operations costs, inventory costs, lead time, processing time, setup time and productivity are the most conclusive relationships identified in the cost section of this study, showing high agreement amongst scholars. Utilizing the five categories of product complexity measures and the results from the coding analysis, Figure 3 was constructed to display the PC→OP relationships where a clear negative linear, U-shaped, or inverted U-shaped relationship was identified. Structural PC measures were the most researched, and thereby, had some of the most conclusive relationships with different OP measures.
When reflecting on the total literature set, it is logical that similar results for time and cost performance were found as measures of time performance and cost performance are related. For example, a product requiring more processing time or lower productivity will also likely have higher manufacturing costs. This link between time and cost performance explains why some of the mediating and moderating factors appear in both sections: demand variability and forecast bias (Abernathy et al., 2000; Benjaafar et al., 2004; Koh et al., 2005), product and component similarity (Brahm et al., 2017; Busogi et al., 2017; Wan, 2016), use of lean manufacturing (MacDuffie et al., 1996; Squire et al., 2006), worker experience and skill level (Anderson, 1995; Brahm et al., 2017), machine flexibility (Nandkeolyar and Christy, 1992), and production sequencing (Berry and Cooper, 1999; MacDuffie et al., 1996). The discussion of increased supply chain coordination costs (or transaction costs) arising from high levels of PC was also discussed in multiple studies as one of the mechanisms underlying the PC → OP relationship (Ahmad and Shroeder, 2001; Ittner and MacDuffie, 1995; Jacobs and Swink, 2011). While quality and delivery performance measures are more distinct from time and cost measures, the underlying mechanisms of time and cost performance also apply to quality and delivery performance.
The studies of PC’s impact on operational costs and time performance in manufacturing and supply chain firms provide clear support for a unidirectional, negative, linear relationship, with some authors finding more nuanced relationships such as an inverted U-shape relationship (Wan, 2016; Wan and Dresner, 2015). The difference between a linear and an inverted U-shape PC→cost relationship is important to understand as it changes the method of management. A negative linear PC→cost relationship logically suggests that management should simply reduce PC and expect an equivalent reduction in costs. In contrast, an inverted U-shape curve suggests that adding variety beyond the vertex of the parabolic curve would be beneficial for the firm, generating economies of scope. This echoes the idea from marketing literature of greater unrelated variety causing worse performance and greater related variety improving performance (Palich et al., 2000; Wu et al., 2012). The exact shape of the relationship is likely to differ across firms based on the homogeneity or heterogeneity of their product assortments.

The few positive relationships that were identified were explained by the authors as either being anomalies (Eckstein et al., 2015; MacDuffie et al., 1996; Moreno and Terwiesch, 2017) or attributed to specific product variety management capabilities, such as machine flexibility (Gupta and Srinivasan, 1998; Ruiz-Torres and Mahmoodi, 2007). Given the weight of observations supporting a negative PC→OP relationship, it is unlikely that increasing performance with increasing product variety and complexity is the norm for most manufacturers.

Data for the cost analysis came primarily from case studies of production systems, such as the two study triads which investigated automotive manufacturers (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996) and beverage distribution firms (Wan, 2016; Wan and Dresner, 2015; Wan and Sanders, 2017). The studies which had access to production data from actual firms usually differentiated their PC measures to meet the needs of the specific production contexts. Though detailed product variety and complexity measures led to the inconclusive, ungeneralizable relationship between composite PC measures and costs in Figure 3, each case offered rich knowledge of very specific cost drivers related to PC, giving practical guidance to management on which types of variety which should be controlled.

The results of the industry analysis showed a dominance of the automotive and electronics manufacturers in the studies, two of the first industries to experience mass customization and the influx of product variants into assembly line manufacturing systems (Squire et al., 2006). This explains why the two industries are represented most in the literature sample. The underrepresentation of apparel, medical, and optical device manufacturers in the literature analyzed is surprising given the rise in customized footwear and medical devices (ElMaraghy et al., 2013; McIntosh et al., 2010; Squire et al., 2006). Further, the results revealed process industries operating with continuous production systems are underexplored in the product variety literature compared to manual batch assembly processes. While their level of PC at process industry firms is not comparable to that of the automotive industry, process industry firms are seeing rising levels of variety in customer demand (William L Berry and Cooper, 1999; Denton, Gupta and Jawahir, 2003; Tang and Huang, 2007; McIntosh et al., 2010) which warrants research into the PC and OP relationship in process industry firms. Anderson and Sedatole (2012) explore this in contextualizing the key variety factors in float glass production and show how only certain parameters had longer setup times (i.e. color and thickness). These insights illuminate the key features which impact performance and represent the contextual factors that Bausch and Pils (2009) call for in the diversity-performance literature. There is further opportunity for learning from the automotive sector to be applied to process industries in the field of product complexity and variety management.

Clustering studies in specific industries which use similar PC and OP measures makes it easier to compare, contrast, and generalize findings on PC→OP relationship. One industry-specific
finding resulting from a clustered set of studies is that parts complexity in the automotive industry has a consistent, negative effect on productivity while model mix and options content have very little effect (Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; MacDuffie et al., 1996). This information helps managers to be careful in adding new parts, such as new wire harnesses while being more open to additional car models or options.

The eighteen studies involving large production or survey datasets from many production firms employed quantitative techniques where PC as either an independent or control variable in the study and measures of OP as dependent variables. However, it was seen that where PC was used as a control variable rather than an independent variable, the article was less likely to find a statistically significant PC→OP relationship (Bortolotti et al., 2013; Christensen et al., 2007; Eckstein et al., 2015; Helkiö and Tenhiälä, 2013). The exact reason for this is unknown, but it could be due to issues in designing PC constructs or that PC becomes less significant in the presence of more dominant variables.

While authors argue that similarity in product and component variants may increase the efficiency of supply chain operations due to synergies in production and logistics (Brahm et al., 2017; Wan, 2016; Wan and Dresner, 2015; Zhang et al., 2007), others show that greater similarity between components in assembly operations leads to greater choice complexity and higher processing time (Busogi et al., 2017). Determining the right level of PC to offer which minimizes the choice complexity and maximizes synergies in the supply chain is a future area of research.

This study has its limitations. Comparing studies from different academic domains with differing methodologies, measurement methods, and industry cases should be done with caution since access to the raw data used in each article is limited (Tranfield et al., 2003). Further, a high frequency of occurrence for a given PC→OP relationship was interpreted as a trend, but the generalizability of the relationships might not extend beyond the cases from which it is drawn. A further limitation of this study is the sample size of 43 articles. While the articles were thoroughly screened and coded, it could be that the criteria were too stringent or that the relevant contribution of the article was not reflected in its abstract. Finally, some papers contributing to this field were written before 1992 which may have added richness to the study, including Kekre and Srinivasan (1990) who found lower manufacturing costs linked to broader product lines in large US manufacturers.

5. Conclusion

This study presents a systematic literature review of the recent scholarly literature on product complexity and operational performance. Responding to manufacturers which must understand the impact of expanding product lines on their systems, researchers have birthed a growing body of insights regarding product variety and the mechanisms through product complexity affects operational performance. In the final literature sample of 93 articles from the past 25 years of research, product complexity showed a consistently negative relationship with manufacturing operational performance across cost, time, quality, and delivery performance measures. However, the evidence supporting the relationships with quality and delivery performance are not as strong as the relationships with cost and time performance measures. Literature coding revealed near-consensus on the negative impact of product variety on general manufacturing costs, inventory costs, lead time, processing time, setup time, and process productivity. Delivery and quality appear the most under-researched performance measures and have the most inconclusive relationships with product complexity.

The negative impact of variety on most performance measures is a phenomenon experienced across industries and is a word of warning for manufacturers seeking to expand product lines.
Before a firm invests in a variety-enabling strategy in operations, such as postponement, the firm could investigate the different levels of product complexity and how they affect their key performance indicators. Firms should also consider adding product variants similar to existing product variants, thus imposing a lower cost on the system. In the academia, researchers should include detailed variety measures specific to the industry-context when assessing the impact of variety on performance measures, as these revealed the most insightful findings in the literature review. Future research areas include investigating the relationship between product complexity and operational cost and time performance to understand when the relationship is linear and when it is logarithmic or quadratic.

References


## Appendix A: Manufacturing Operational Performance Measures Identified in Literature

### Table 5. Manufacturing Operational Performance Measures Identified in the Literature Sample

<table>
<thead>
<tr>
<th>Manufacturing Operational Performance Measure</th>
<th>Definition</th>
<th>Publication</th>
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<tbody>
<tr>
<td><strong>Costs</strong></td>
<td></td>
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</tr>
<tr>
<td>Manufacturing costs (general)</td>
<td>Cost of production for one product (e.g. costs of material, labour and machine processing, and tooling)</td>
<td>(Alford et al., 2000; Berman, 2011; Lanza et al., 2010; Moreno and Terwiesch, 2017; Silveira, 1998; Sun and Ding, 2010; Wong and Eyers, 2011; Zhang and Tseng, 2007)</td>
</tr>
<tr>
<td>Manufacturing and logistics costs</td>
<td>Manufacturing and logistics costs (e.g. packaging, inventory holding, distribution, logistics)</td>
<td>(Ding et al., 2007; Roy et al., 2011; Wan, 2016; Wan and Dresner, 2015)</td>
</tr>
<tr>
<td>Direct manufacturing costs (survey)</td>
<td>Manufacturing costs relative to competitors, normalized 5 or 7 pt. Likert scale</td>
<td>(Bozarth et al., 2009; Helkio and Tenhiälä, 2013)</td>
</tr>
<tr>
<td>Manufacturing and other costs (survey)</td>
<td>Costs relative to competitors, including design, manufacturing, component, delivery, and servicing costs, 5 pt. Likert scale</td>
<td>(Van Den Broeke et al., 2015; Caniato and Größler, 2015; Eckstein et al., 2015; Squire et al., 2006)</td>
</tr>
<tr>
<td>Added value (ranked)</td>
<td>Manufacturing cost - added value per GBP of employee cost, ranked within sample</td>
<td>(Mapes et al., 1997)</td>
</tr>
<tr>
<td>Unit and inventory cost</td>
<td>Unit costs at retailer, inventory holding costs, and backorder costs</td>
<td>(Thonemann and Bradley, 2002)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Survey measure of unit manufacturing cost, inventory turns, and cycle time</td>
<td>(Bortolotti et al., 2013)</td>
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<tr>
<td><strong>Direct labour costs</strong></td>
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<tr>
<td>Direct labour costs</td>
<td>Direct labour hours per unit produced, measure of the value adding activities</td>
<td>(Fisher and Ittner, 1999; Ittner and MacDuffie, 1995)</td>
</tr>
<tr>
<td>Labour productivity</td>
<td>Hours of working effort per part</td>
<td>(MacDuffie et al., 1996)</td>
</tr>
<tr>
<td>Manufacturing Overhead</td>
<td>Cost of indirect factory personnel</td>
<td>(Anderson, 1995; Anderson and Sedatole, 2012; Brun and Pero, 2012; Fisher and Ittner, 1999; Ittner and MacDuffie, 1995; Scavarda et al., 2010)</td>
</tr>
<tr>
<td><strong>Inventory costs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inventory cost</td>
<td>Sum of holding costs (some include backorder costs)</td>
<td>(Abbey et al., 2013; Abernathy et al., 2000; Appelqvist et al., 2013; Benjaafar et al., 2004; Brabazon et al., 2010; Escobar-Saldívar et al., 2008; Fisher and Ittner, 1999; Moreno and Terwiesch, 2017; O’Reilly et al., 2015; Pil and Holweg, 2004; Seifoddini and Djassemi, 1996; Wan and Sanders, 2017; Ward et al., 2010)</td>
</tr>
<tr>
<td>Supply-Demand Mismatch costs</td>
<td>Cost of discounting inventory due to oversupply, calculated as manufacturing spend on incentives</td>
<td>(Moreno and Terwiesch, 2017)</td>
</tr>
<tr>
<td>Inventory and capacity costs</td>
<td>Costs of inventory, cycle stock, and capacity purchase costs from external suppliers</td>
<td>(Rajagopalan and Swannanathan, 2001)</td>
</tr>
<tr>
<td><strong>Time</strong></td>
<td></td>
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<tr>
<td>Lead time (general)</td>
<td>Time from order to delivery, includes design time if a custom product</td>
<td>(Akin and Meredith, 2015; Akkerman and van Donk, 2007, 2009; Berman, 2011; Brabazon et al., 2010; Christensen et al., 2007; Holweg, 2005; Inman and Blumenfeld, 2014; Vilas and Vandaele, 2002; Ward et al., 2010; Wong and Lesmono, 2013; Xia and Rajagopalan, 2009; Zhang et al., 2007)</td>
</tr>
<tr>
<td>Lead time (quoted, ranked)</td>
<td>Avg. lead time quoted to customer, ranked within sample</td>
<td>(Mapes et al., 1997)</td>
</tr>
<tr>
<td>Lead time (expected)</td>
<td>Expected lead time for order fulfilment</td>
<td>(Thonemann and Bradley, 2002)</td>
</tr>
<tr>
<td>Lead time (survey)</td>
<td>Average lead time relative to competitors, questions measured on Likert scale</td>
<td>(Caniato and Größler, 2015; Squire et al., 2006; Vachon and Klassen, 2002)</td>
</tr>
<tr>
<td>Responsiveness (backlog)</td>
<td>Number of items currently being worked on by the facility, used to indicate lead time</td>
<td>(Gupta and Srinivasan, 1998)</td>
</tr>
<tr>
<td>Flexibility</td>
<td>Survey measure including sub measures of ability to adjust orders last minute and reduce lead time</td>
<td>(Blome et al., 2014; Caniato and Größler, 2015)</td>
</tr>
<tr>
<td><strong>Process Time</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Order and process time</strong></td>
<td>Time from order to finish of manufacturing</td>
<td>(Er and MacCarthy, 2006)</td>
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<td>-------------------------------------------</td>
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</tr>
<tr>
<td><strong>Process time</strong></td>
<td>Time to assemble or process a product in manufacturing</td>
<td>(Busogi et al., 2017; Deane and Yang, 1992; Djassemi, 2005; Engström et al., 1995; Gupta and Goyal, 1992; Huang and Inman, 2010; Jensen et al., 1996; Keil et al., 2014; Nagarur and Azeem, 1999; Nazarian et al., 2010; Ruiz-Torres and Mahmoodi, 2007, 2008, Serfoziddini and Djassemi, 1996, 1997; Yang and Deane, 1993; Zhang et al., 2007)</td>
</tr>
<tr>
<td><strong>Processing time (survey)</strong></td>
<td>Processing time based on survey responses</td>
<td>(Vachon and Klassen, 2002)</td>
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</table>

**Setup Time**

| Setup Time | Time used to set up machinery for product change | (Anderson, 1995; Brun and Pero, 2012; Cusumano, 1994; Escobar-Saldívar et al., 2008; Kampker et al., 2012; Sardar and Lee, 2015) |
| Run length / lot size | Production run length (e.g. total sales divided by number products, or batch size) | (Baldwin et al., 2012; Celano et al., 2012) |
| **Batch size** | The volume of product produced per batch | (Berry and Cooper, 1999) |

**Productivity**

| Process productivity | Throughput, saleable product produced per hour production | (Aw and Lee, 2009; Berry and Cooper, 1999; Nagarur and Azeem, 1999; Nandkeolyar and Christy, 1992) |
| **Downtime** | Minutes producing non-saleable product per day | (Anderson and Sedatore, 2012) |
| Total factor productivity | Reduction in average costs not accounted for by change in input prices (i.e. labour and efficiency related) | (Alvarez et al., 2016; Gollop, 1997) |
| Log of volume | Natural logarithm of production volume | (Brahm et al., 2017) |
| **Speed** | Production speed | (Silveira, 1998) |

**Quality**

| Quality (general) | Product quality | (Berman, 2011; Silveira, 1998) |
| Product recalls | Number of product recalls | (Shah et al., 2017; Thirumalai and Sinha, 2011) |
| **Product performance (survey)** | Product performance relative to competitors, 3 questions with 7 pt. Likert scale, normalized | (Helkiö and Tenhula, 2013) |
| Quality (survey) | Quality durability, reliability, and others such as conformance, % returns, and % final pass inspection, relative to competitors, questions measured on 5 pt. Likert scale | (Caniato and Größler, 2015; Squire et al., 2006; Thomé, Sousa and Scavarda do Carmo, 2014) |
| Customer returns (ranked) | Customer returns % of output, ranked within sample | (Mapes et al., 1997) |
| **Product reliability** | Customer rank from consumer reports | (Novak and Eppinger, 2001) |
| Human errors | Number of human errors in production | (Brun and Pero, 2012) |
| Rework | % or parts requiring rework | (Fisher and Ittner, 1999) |
| **Defects** | Number of defects per 100 vehicles due to assembly | (MacDuffie et al., 1996) |
| Mismatch errors | Errors seen in the field by customers where customization did not meet the performance desired by the customer (design errors) | (Hegde et al., 2005) |
| **Manufacturing errors** | Errors where manufacturing process is not capable of achieving the constraints set by the customer | (Hegde et al., 2005) |
| **Repair costs** | Function of repair costs of products built | (Huang and Inman, 2010) |
| **Inspection costs** | Costs of inspection | (Celano et al., 2012; Huang and Inman, 2010) |
| Yield | Percentage of good products coming from a process | (Hsieh and Tong, 2006; Kadakia et al., 1994; Maruthi and Roshan Joseph, 1999) |

**Delivery**

<p>| Delivery Performance (survey) | Delivery performance relative to competitors, 3-7 questions with Likert scale, normalized | (Bortolotti et al., 2013; Helkiö and Tenhulää, 2013; Rosenzweig, 2009; Tracey, 2004) |
| On-time delivery | % orders delivered on time | (Ahmad and Shroeder, 2001; Appelqvist et al., 2013) |
| On-time delivery (rank) | % items delivered on time, ranked within sample | (Koh et al., 2005; Mapes et al., 1997) |
| <strong>Delivery reliability (survey)</strong> | Delivery reliability, speed, lead time, and % on time relative to competitors, survey questions, Likert scale | (Caniato and Größler, 2015; Squire et al., 2006; Thomé, Sousa and Scavarda do Carmo, 2014; Vachon and Klassen, 2002) |</p>
<table>
<thead>
<tr>
<th>Measure</th>
<th>Definition</th>
<th>Source(s)</th>
</tr>
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<tbody>
<tr>
<td>Lead time variability</td>
<td>Variance in lead time, survey</td>
<td>(Christensen et al., 2007)</td>
</tr>
<tr>
<td>Order fulfilment rate</td>
<td>% of orders fulfilled completely</td>
<td>(Closs et al., 2010; Wan et al., 2012, 2014)</td>
</tr>
<tr>
<td>Unit fill rate</td>
<td>% of line items fulfilled completely</td>
<td>(Appelqvist et al., 2013; Closs et al., 2010)</td>
</tr>
<tr>
<td>Quality and delivery performance</td>
<td>Performance on product quality, service level, and on-time delivery compliance, 5 pt. Likert scale</td>
<td>(Eckstein et al., 2015)</td>
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**STUDY C**

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<td>Alexandria (Moseley) Trattner, Lars Hvam and Zaza Nadja Lee Herbert-Hansen</td>
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OPERATIONAL IMPACT OF PRODUCT VARIETY IN THE PROCESS INDUSTRY

Alexandria Moseley, Lars Hvam and Zaza Nadja Lee Hansen
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Abstract: The purpose of this research article is to examine the impact of product variety on production performance in the process industry. As the number of product variants sold by a process company typically impacts the run length, production data from a mineral wool insulation manufacturer is analyzed to quantify the impact of longer runs on productivity. In testing the hypothesis that longer runs lead to higher productivity, the results show that the number of variants in itself is not a sufficient parameter to explain the variation in production performance; rather, the different types of product variants and their production sequence must also be considered. Based on the findings, a method for quantifying the production cost of product variety in the process industry is developed, adding to the literature a rich case showcasing factors which influence production performance and the impact is measured with metrics.

Keywords: Complexity, Production Performance, Process Industry

1. INTRODUCTION

The plight of increasing product variety and process complexity is a reality for manufacturing companies as businesses have become more global and customers have demanded more customized products. As the level of customized products has grown, the production processes used in industry have transformed, moving from craft production in the 1800’s to mass production and the early 20th century and now to mass customization in the late 20th and early 21st centuries [1]. The recent shift to mass customization has brought with it greatly increased product variety to customers, but also greater challenges to manufacturers in order to produce greater variety. While product variety should be added in a way that adds the most value to the customer, the profitability of doing so must also be considered [2]. To remain competitive, manufacturing companies in many industries must determine the appropriate amount of product variety to offer within their product range to both satisfy customer needs and keep low production costs. This first requires a firm understanding of how product variety impacts the complexity of production processes.

From an industry perspective, complexity caused by increased product variety and other factors is one of the top issues faced by companies in the process industry. A survey of managers at chemical companies and process companies revealed that 72% of managers consider complexity management one of their top priorities in running their business [3].

Offering greater product variety poses a particular challenge in the process industry where increased product variety can lead to reduce batch sizes, increased setup and changeover time, increased waste and lower productivity [4]. The costs of these inefficiencies are particularly high in the process industry due to the high cost of capital equipment in the production processes and the long changeovers required between production runs [5].

Various methods have been presented in the literature for quantifying the impact of product variety on production performance in the process industry [6], but these have been largely based on sophisticated regression techniques and optimization models. What is missing is the link between these techniques and operational rules which can be implemented easily in production and production planning departments. This article aims to bridge this gap by creating an operational procedure for calculating the impact and costs in production due to increased product variety.

To further investigate the situation for process industry companies facing increased product variety, the following research question has been developed to guide the study: what is the impact of product variety on production performance in the process industry?

The American Production and Inventory Control Society (APICS) defines process industries as “businesses that add value to materials by mixing, separating, forming or chemical reactions [which] may be either continuous or batch and usually require rigid process control and high capital investment” [7]. These companies produce materials such as glass, ceramics, stone, clay, steel, metal, chemicals, food, beverages, textiles, lumber, wood and pulp and paper [8]. One of
the distinctive characteristics of a company in the process industry is the production of high volume products with low variety using mass production systems.

Product variety is here referred to as the number of finished end items produced. The number of finished end items has been used as a measure of product variety in various operations management studies within different business areas, including sales, production, and warehousing [6][9][10].

This paper is structured as follows: first, literature is reviewed which covers the topics of product variety and the process industry; next the methodology of mixed methods is presented followed by an analysis of the findings at the case company. To close, conclusions are presented and future work is suggested.

2. LITERATURE

The issue of product variety in the process industry is underexplored compared to the automotive and electronics industries, which were some of the first to adopt the strategies of mass customization [1] [11] [12] [13]. A list of selected studies of product variety on performance in the process industry includes:

- Impact on productivity and margin at a chemicals company [4],
- Impact on inventory and scheduling at a plastics company [6],
- Impact on quality, service, flexibility and dependability in batch and continuous manufacturing companies [14], and
- Impact on inventory costs at a soft drink company [9].

The level of product variety can directly impact the performance of production measured in performance indicators such as throughput, machine utilization, average run length, quality of goods produced, and changeover time [4]. Achieving a high utilization is one common objective in the process industry as maximizing output minimizes production costs per unit [5].

The work of Berry and Cooper [4] provided a method for assessing the effects of increased product variety on manufacturing performance in the process industry. In their study of chemical manufacturer, they used regression analysis to assess different factors influencing production performance in the process industry. They found that smaller batch sizes caused by increased product variety resulted in lower productivity levels for some cases at the company, however there were processes for which there was no relationship between the two measures. This leaves an open question of whether or not product variety impacts productivity.

Besides linear regression, other methods of analysis such as operations research models have been developed for studying the impact of variety on production. Cooke and Rohleder [6] adapted an economic lot sizing model for discrete processing industries to fit the unique changeover waste loss in the process industry. This study revealed that production scheduling in the process industry is a particular issue as the production runs can be very long and have a high value in terms of finished product [6].

The process industry is selected for analysis due to the limited work present in this area on quantifying the impact of product variety on process complexity in production. Orfi, et al. [15] conclude in their literature review that very little research has been performed in regard to the complexity of the product in process industries (e.g. glass, food, petroleum products). They note that interdependence level between components in these industries is higher which can affect the overall complexity within the system. There is a challenge in studying these products made in the process industry since many of the processing occurs at the molecular level, making the interactions between components difficult to visualize. Product variety has been shown to have a higher impact on costs for continuous processing companies than for flow shop and project organizations [14], thus motivating further study in this area.

As the process industry is typified by having expensive industrial processes in the production phase [5], this study will focus on the impact of complexity on production. Quantifying how much more product variety impacts costs will be the focus of this article. The impact of product variety on other areas of the supply chain is not considered since we assume that there is no impact on production performance, which is the primary focus of this article.

While methods for assessing the impact of product variety on the performance of manufacturing systems are presented in the existing literature, the methods have little testing at companies within the process industry and require further validation to ensure applicability to different production systems. Additionally, the methods present do not provide an operational way to implement the findings regarding the quantified impact of shorter runs or production sequence in operations. For example, Berry and Cooper [6] provide equations for the calculation of contribution margin impact for a given productivity level, but offer no steps for achieving and monitoring increased output.

The purpose of this paper is to examine the interaction between product variety and manufacturing performance in the process industry and add value in industry by creating an operational tool by which decision makers can review their production plans and product assortments to be more profitable.

3. METHODOLOGY

To answer the research question and determine the impact of product variety on production performance in the process industry, a mixed methods approach is taken which uses both quantitative and qualitative data from a case company [16]. The analysis will be primarily quantitative using descriptive statistics and regression
analysis. Qualitative data acquired using semi-structured interviews with relevant employees will be used to supplement and interpret the quantitative data.

Data on production performance was gathered from the enterprise resource planning system and the manufacturing execution system at the case company while cost data was obtained from accounting databases. For the semi-structured interviews, four production planners were interviewed once each to obtain knowledge about the production sequencing at Insulation Company. Three, half hour interviews were conducted with a manufacturing data specialist in order to understand the logic of the manufacturing execution system and correctly interpret the production data. Two, half hour interviews with finance controllers at the company were also performed to understand the cost structure in production.

The case company chosen is a manufacturer of mineral wool insulation materials, referred to as Insulation Company, with sales and production in North America, Europe and Asia. Insulation Company was chosen due to its presence in the process industry and difficulty with managing the production of an increasing product assortment. Managing product-variety and process complexity has been a focus at the company since 2011 after their number of stock keeping units (SKUs) increased noticeably in the early 2000s.

Mineral wool production is an energy intensive process involving the melting of stone, spinning of mineral wool fibers, lamination of the fibers into wool and then curing, slicing and packaging the wool into finished goods. This process is shown in Figure 1 and consists of a single process flow. The main production line is characterized as a continuous production system as the product is homogenous until the cutting step. After cutting, the product takes a discrete form in which it is packaged and sold.

![Diagram of Mineral wool production process](image)

**Figure 1. Mineral wool production process**

### 3.1 Hypothesis

A hypothesis for this research question was developed to explore the impact of range complexity on a single measure of operational performance: process time productivity (equal to the saleable output/process time). Since producing greater variety on the same production system implies smaller batch sizes and shorter run lengths, production run length is used as an indicator of the level of product variety at the company. The hypothesis and alternative hypothesis is modeled after the third hypothesis in the work of Berry and Cooper [4] to measure the change in productivity for the process.

- **H1**: Production run length and process time productivity (tons saleable output/(process time)) are not related.
  - **H1A**: Production run length and process time productivity have a positive relationship (i.e. process time productivity increases as run length increases).

Terms relating to product variety complexity and the process industry are described below.

- **Product variety** – the number of unique products made on the production line.
- **Changeover waste** – the non-saleable product produced before a production run when transitioning from the previous production run of a different product.
- **In-sequence** – a term used to denote that a production run has been scheduled in the preferred sequence as detailed by the production planners at the company (e.g. products from same product family which are scheduled successively).
- **Process time** – (i.e. run length) the time the machine is producing both saleable product and waste product for a given production run. This does not include down time due to a production stop, missing materials, etc.

Process time productivity was selected because it serves as a direct measure of the efficiency of the production line and an indirect measure of the amount of changeover waste generated before a production run. This measure excludes the downtime experienced in a given run, thus reducing the noise in the data. Additionally, process time productivity is one of the key performance indicators used at Insulation Company which will make the findings easier to translate into practical actions and improvements in production.

### 3.2 Multiple regression analysis

To test this hypothesis, regression analysis will be applied to production data from one production line at Insulation Company in order to discern the relationships between the product variety and production performance. The production line selected for analysis is located in central Europe and it produces a level of product variety that is representative of the product portfolio at the company. The line is also currently running at full capacity and management is interested in understanding how more volume can be produced and less waste generated on this resource.

For the production line examined in this study, 1,106 production runs were selected from 2015 data for analysis (see Table 1). The runs selected represent the
three major product families (PFs) made on the production line and are representative of the product mix produced on the line. Data was cleaned of the production runs with unusually high or low productivity rates due to assignable causes (i.e. a production stop, quality issues, etc.). Approximately 18% of the runs being assessed were scheduled out of the natural sequence as defined by production planners. The selected runs for each PF have varying run lengths to better calculate the impact of run length on production performance.

Reviewing the overview statistics for the runs selected, it can be seen that PF 1 has the most production runs and production volume of the three selected products. Product family 2 is produced with half the frequency of PF 1 but with one tenth the volume of PF 1 and significantly shorter run lengths. Product family 3 has the second highest volume in the runs selected, but has the lowest number of production runs and number of products. This is due to the nature of the four products in PF 3 being used as input for further processing on a different line, thus being scheduled in long runs. As the runs in PF 3 have a long run length, the planners are able to schedule them in the natural sequence more than the other PFs which are produced more frequently.

Table 1. Production run characteristics for 3 product families assessed in one production line

<table>
<thead>
<tr>
<th></th>
<th>All Runs</th>
<th>PF 1</th>
<th>PF 2</th>
<th>PF 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production runs</td>
<td>1,106</td>
<td>688</td>
<td>299</td>
<td>119</td>
</tr>
<tr>
<td>Production runs out of sequence (% and % of production runs)</td>
<td>902 (18%)</td>
<td>125 (18%)</td>
<td>67 (22%)</td>
<td>12 (10%)</td>
</tr>
<tr>
<td>Products analyzed</td>
<td>128</td>
<td>89</td>
<td>35</td>
<td>4</td>
</tr>
<tr>
<td>Production volume (% total)</td>
<td>40%</td>
<td>31%</td>
<td>3%</td>
<td>6%</td>
</tr>
<tr>
<td>Average run length (hours)</td>
<td>2.38</td>
<td>2.99</td>
<td>0.59</td>
<td>3.33</td>
</tr>
</tbody>
</table>

3.3 Model development

The regression model developed for process time productivity at Insulation Company takes the following form:

\[ Y = B_0 + B_1 \ln(X_1) + B_2X_2 \]  

(1)

Where:

- \( Y \) is the process time productivity,
- \( X_1 \) is the run length in hours and
- \( X_2 \) is a binary variable which indicates if the production run was scheduled in or out of the natural sequence (1 indicates that the run was scheduled in the natural sequence; 0 indicates that the run was scheduled out of the natural sequence).

To create the regression model, the independent variable of primary interest, run length, was added first and tested for fit. A logarithmic fit of the run length was determined as the best representation of the data points for productivity. This was considered reasonable for productivity since there is a maximum output for a machine which the performance measurements will naturally converge to.

To further explain the variability in the data for process time productivity, other variables were added and removed using forward selection [17] in order to create a model with a parsimonious fit. Variables tested for inclusion in the model were the sequence of the product, seasonality coefficient, product density, and the process time efficiency of the previous production run. Seasonality was not included since no trend was identified in the data showing differing run lengths for the high season compared to the low season. The density variable was found to be significant in initial model and with the density values being split into three distinct groups based on product family; therefore, the data set was split into three subsets in order to discern the differences between the product families.

4. ANALYSIS

The hypothesis stated above was tested by applying the model in equation (1) to four sets of the data: all production runs, PF 1 production runs, PF 2 production runs, and PF 3 production runs. All regressions were conducted at the 0.05 significance level. The regression results are shown in Table 2.

For the full data set, the regression results show that the coefficients for both run length and sequence are positive and significant at the 0.05 significance level. However, testing each of the PFs in isolation shows that there are different relationships for each family. For PF 1, both run length and sequence are very significant; for PF 2, neither run length nor sequence is significant; for PF 3, only sequence is significant. Since this test is meant to uncover the relationships between the variables rather than create a fixed model for the performance of a product family on a given production line, the intercept values were excluded from the table. This was also done to maintain confidentiality for Insulation Company.
Table 2. Regression results for process time productivity 3 product families

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std. Error</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>All products - Process time productivity (kg/hr)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.042</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F value/significance F</td>
<td>25.2</td>
<td>34.2</td>
<td>0.004*</td>
</tr>
<tr>
<td>Ln(Run length) coefficient</td>
<td>98.2</td>
<td>97.8</td>
<td>0.000*</td>
</tr>
<tr>
<td>In sequence coefficient</td>
<td>635</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| PF 1 – Process time productivity (kg/hr) |        |            |              |
| Adjusted R²          | 0.161  |            |              |
| F value/significance F | 67     | 42.3       | 0.000*       |
| Ln(Run length) coefficient | 356    | 110        | 0.000*       |
| In sequence coefficient | 950    |            |              |

| PF 2 – Process time productivity (kg/hr) |        |            |              |
| Adjusted R²          | 0.000  |            |              |
| F value/significance F | 1.04   | 135        | 0.310        |
| Ln(Run length) coefficient | 137    | 212        | 0.324        |
| In sequence coefficient | 209    |            |              |

| PF 3 - Process time productivity (kg/hr) |        |            |              |
| Adjusted R²          | 0.081  |            |              |
| F value/significance F | 6.21   | 119        | 0.248        |
| Ln(Run length) coefficient | 139    | 261        | 0.001*       |
| In sequence coefficient | 875    |            |              |

* Indicates significance at the 0.05 significance level

Figure 2. Process time productivity regression results for the full data set (y axis label removed for confidentiality)
A line fit plot for the regression model for all products is shown in Figure 2. The line for the predicted value of process time productivity is divided into two lines where the upper line represents the expected productivity for runs that are scheduled in the natural sequence and the lower line represents the predicted values for the runs which are out of the natural sequence. It can be seen that variability in the process time productivity of shorter runs is much higher than for longer runs.

The Adjusted R squared terms are lower than one would expect for a linear regression due to the high variation in the data, particularly for the lower run lengths under 60 minutes. Despite this variation, valuable insights can still be gained from the analysis of the statistically significant factors of run length and sequence.

The data was tested for independence and normality in line with the assumptions of linear regression [17]. The data showed deviations from normality with extreme high and low values creating heavy tails in the distribution. This can be attributed to the fact that this data was collected in an actual production environment and is subject to many factors which influence the productivity. However, the plot does appear linear in the middle of the graph indicating normality for a large set of the data. The residuals for the models, while having a slightly higher variance for low run lengths, have a mean of zero for the four tests and show no upward or downward trends.

5. DISCUSSION

By looking at the four p-values for the run length regression coefficients, only two of the four are below the 0.05 significance level: the coefficient for whole data set and the coefficient for the PF 1 subset of data. This leads us to reject the null hypothesis for the full data set and the PF 1 data set and fail to reject the null hypothesis for the PF 2 and PF 3 data sets.

The reasoning why the run length coefficient was only significant for one of the three PFs is not directly obvious. Two of the possible causes are inconsistencies in the data for the selected runs and the fundamental differences in the product properties between the product families. Regarding the nature of the data, the sample of runs for PF 1 is the largest of the three PFs, which could create a dominating effect on the result for the first and second regression analyses. For PF 2, the sample of runs selected for analysis were shorter than those for PF 1 and PF 3, which in turn implies that the process time productivity had greater variability. This greater variability in productivity for shorter runs makes it difficult to identify a relationship for the independent variables in the regression for PF 2. Perhaps if the runs for this product family were longer, the relationships between the two independent variables, run length and sequence, would have had a greater impact on the process time productivity, but it is not possible with the given data set.

In regards to the differences between product families, the primary product characteristic distinguishing the three families here is the product density. The interviews with the production planners revealed that changing the product density on the production line requires some of the largest changes in the equipment settings. Further comments from the planners suggested that the different PFs were scheduled with different rules of thumb to avoid reducing the output rate on certain machines. This suggests that the physical characteristics of the PFs are one of the causes for the significance or lack of significance of the run length coefficient, and thus one of the factors which determine the impact of product variety on productivity at Insulation Company.

Interesting findings were uncovered regarding the production sequence, despite the fact that it was not the primary independent variable analyzed in this study. The sequence coefficient showed to be a statistically significant factor in determining productivity in all regressions except the PF 2 regression. While the coefficient values for the natural logarithm of the run length are difficult to interpret without transforming the data, the sequence coefficients are more intuitive, representing the increase in output obtained when a production run is scheduled in the natural sequence compared to if it had been scheduled out of the natural sequence. The results from Table 2 show that productivity for PF 1 and PF 3 increases by 875-950 kilograms per hour when the production run is scheduled in the natural sequence. This was shown to be even higher in PF 1 and PF 3.

As these runs were taken from throughout the full year 2015 and were representative of the products typically made in this product family, it is reasonable to extend this quantified correlation to the whole product family.

5.1 Calculating the impact of product variety

Now that the relationship between product range complexity and production performance has been determined, a method for quantifying the detailed production cost of product range complexity in the process industry can be created. Using the results of the regression, Table 3 was created which shows the percentage increase in productivity achieved for PF 1 when run lengths are increased in different time increments. The percentages were calculated by taking the productivity rate for a given run length divided by the approximate maximum productivity rate obtained from the regression model (i.e. the process time productivity for a 5 hour run) and then taking the difference between the percentages for each pair of run lengths. Increasing the run length of small runs has an immediate impact on process time productivity since these runs are the most affected by changeover waste.
Table 3. Percentage increase in process time productivity for PF 1 by increasing run length

<table>
<thead>
<tr>
<th>To run length:</th>
<th>From run length:</th>
<th>0.5 hour</th>
<th>1 hour</th>
<th>1.5 hours</th>
<th>2 hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25 hour</td>
<td>2%</td>
<td>4%</td>
<td>6%</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td>0.5 hour</td>
<td>-</td>
<td>2%</td>
<td>3%</td>
<td>4%</td>
<td></td>
</tr>
<tr>
<td>1 hour</td>
<td>-</td>
<td>1%</td>
<td>2%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.5 hours</td>
<td>-</td>
<td>-</td>
<td>1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 hours</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This data and knowledge of the production process were integrated into a simulation of the cost impact of increasing run lengths. First, analysis of the direct and fixed costs at Insulation Company was performed to quantify the savings from longer runs, as shown in equation (2). The equation aims to find the increased margin \( \Delta Margin \) (Euros) which results from increased revenue minus decreased costs where \( \Delta Y \) is the change in process time productivity (kg/hour), \( SP \) is the sales price (Euros/kg), \( P \) is the cost of packaging materials (Euros/kg), \( X \) is the sum of the run lengths being adjusted (hours), \( W \) is the cost saved in reduced waste processing (Euros) and \( L \) is the labor cost savings of longer run lengths (Euros).

\[
\Delta Margin = \Delta Y \times (SP - P) \times X + W + L \tag{2}
\]

For other companies, there may be other material costs which should be added, but this was excluded for the Insulation Company in this study since the quantity of raw materials utilized would not change with increasing run length; rather, less waste would be produced. It is also possible to add the costs of extra processing at additional stages of production according to the production system at the company. The quantification method has been created for a production line which is at full capacity with the assumption that the increased output from longer runs would create finished goods that would be sold. This is a safe assumption for the case of Insulation Company, but would need to be assessed in a case by case basis depending on the demand in each company. Also, when utilizing the equation, it should be considered that any labor cost savings due to longer runs should be translated into alternate shift schedules or layoffs.

It was not possible to fully simulate equation (2) at Insulation Company due to the lack of data on the waste processing and labor staffing level changes and the sensitivity of the revenue data. However, it was possible to quantify the effect of increasing all run lengths on the overall output of the production line using the regression output for all products. For example, consolidating all short runs (less 1 hour) for each product to an average run length of 1 hour can increase overall output by 1.1% in the same amount of production time. Increasing the same runs to a 2 hour minimum run length increased output by 1.7%. Further scenarios can be created to establish a minimum run length rule for planners to use so the company can achieve the desired level of output in a given period, thus making the analysis results actionable at the operational level.

It should be noted that this discussion takes a view of the impact of variety on production without consideration for the impact on warehousing. The results of the analysis should be used cautiously and not used to motivate endless increase of run lengths which could increase warehouse costs due to higher inventories.

These findings were synthesized into a 5-step method for the quantification and reduction of product-variety induced production cost in the process industry (see list below).

1. Identify the key factors impacting process time productivity using regression analysis.
2. Apply production cost data to quantify the change in cost based on the key factors.
3. Set a target for improvement in process productivity or production cost (applicable for production lines close to maximum utilization).
4. Create operational rules based on the factors and targets (e.g. target run lengths and sequencing for planners).
5. Track production performance to ensure results are attained and repeat steps 3 and 4 if necessary.

The first step of the framework involves applying regression analysis technique as used in this paper. This step will identify the most influential factors relating to product variety which impact production performance. The second and third steps involve applying the company cost data and setting targets based on their performance ambition level. The fourth step translates the results of the regression into operational methods for production planning and scheduling. This proposed technique is designed for a manual planning process, as was seen in Insulation Company, but can be adapted to fit automated planning systems that are built into ERP software packages. The fifth step is included to follow up on the improvement and embed the knowledge of the extra cost of product variety into work routines at the company.

5.2 Comparison with existing literature

Returning to the research question of the impact of product variety on production performance in the process industry, this study shows that it depends on the product characteristics and the scheduling practices of the company. A low volume product which is scheduled in the right sequence and with a sufficiently long run length could be profitable for a company to produce and not negatively impact production performance. Conversely, a high volume product that is produced in
small runs and scheduled out of the appropriate production sequence can negatively affect the production performance. In the context of existing literature, this finding adds to Christopher’s view that product variety should not only be added so as to increase value to the customer while minimizing internal costs [2], but should also be scheduled to achieve the same objectives. In this case in the process industry, the scheduling of additional products is the main lever determining whether adding an extra product will help or hurt the business [5] [6].

The findings can be seen as comparable to those of Berry and Cooper [4] who found batch size as statistically significant factor affecting the run time productivity for two processes at a chemicals company. However, they neglected to perform an analysis by product family. This study adds the idea that product characteristics (e.g. density) also have an impact on the production performance which may override the benefits of increasing run lengths and lower changeover waste for certain products. Furthermore, this works shows the applicability of the assessment method of Berry and Cooper [4] to alternative production systems such as mineral wool production in the process industry.

6. CONCLUSION

This study sought to assess the impact of additional product variety on production performance in the process industry and calculate the differential production cost incurred by adding product variety and reducing run lengths. The results support that a product-specific view must be taken when analyzing the production data in order determine the impact of variety on production performance, thus extending the analysis framework of Berry and Cooper [4]. In this study, the defining product characteristic by which product families are distinguished is the density of the product. In other process industry companies, viscosity, chemical composition, or mass could be more relevant attributes to investigate.

This paper adds to the work on the operational impact of product variety by illustrating the findings from a case company in the process industry that is previously unstudied. As a case study approach is taken, it will not be possible to extrapolate the findings to all manufacturers in the process industry. The resulting analysis and method for calculating the cost impact of product variety will be relevant to industry as they will assist product managers and production managers determine the most profitable product assortment and scheduling practices to remain competitive.

As future research, the scope of this study could be expanded to incorporate the impact of product variety on secondary stages of processing after the main process is studied. As a difference in production performance was also seen between product families, a more in depth study on how product architectures and process characteristics impact performance in this industry would be an appropriate extension of this work. This study was motivated by the work of Berry and Cooper [4] and their call for researchers to apply their approach to process industry companies beyond chemical manufacturers. Now with the findings of a mineral wool company assessed, as well, it can be equally as valuable to test the method in a company in the food or beverage sector or pulp and paper products company to provide further validation.

7. ACKNOWLEDGEMENTS

A special acknowledgement is owed to Lea Greiling and Fabio Labrini who helped with the data gathering and analysis in this project.

8. REFERENCES


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<td><strong>Paper type</strong></td>
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<td><strong>Outlet</strong></td>
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Which variety is free? Discerning the impact of product variety in the process industry

Alexandria Moseley\textsuperscript{1,2}, Anna Myrodia\textsuperscript{1}, Lars Hvam\textsuperscript{1} and Zaza Nadja Lee Herbert-Hansen\textsuperscript{1}
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Keywords: Product variety, Process industry, Operational performance

Abstract. In the pursuit of mass customization, it is a great challenge for companies to maintain mass production efficiencies while producing a wide range of products. This poses an even greater challenge to process industry manufacturing systems which are built for high volume, low variety operations and which are sensitive to changes in process parameters. Many studies have been performed to quantify the impact of product variety on the efficiency of automotive assembly processes, but little work has been done to address process manufacturing systems. This study aims to determine the effects of individual product features on machine productivity at a process industry manufacturer. A lasso regression model is developed and tested using actual product and process level data from a stone wool manufacturer in central Europe. Results show that product features are less correlated to machine efficiency than process parameters, such as planning and crew performance.

Keywords: Product variety, Process Industry, Operational performance

1 Introduction

On the path to mass customization (MC), meeting ever expanding customer needs in affordable ways becomes imperative for the manufacturing firm. Waves of MC, producing customized products at mass production efficiencies [1], have hit the automotive, electronics, and clothing industries but have yet to hit many manufacturers in the process industry. Process manufacturers typically utilize production systems with high capital investment [2] and complex process variables which make the systems sensitive to product variety required in MC. While companies can regain lost throughput from product variety by understanding production dynamics and enabling more accurate prediction of processing times and sequencing [4], there is an unexplored field combining existing methods with Big Data analysis to determine “which variety is free?” in process manufacturers [3]. The purpose of this paper is to address this gap by presenting a combined assessment of the impact of product features on production throughput (tons of saleable product per effective hour of the production line) at a process manufacturer using lasso regression.
2 Methodology and Preliminary Findings

This project uses lasso regression to approach the problem using data from a mineral wool insulation manufacturer in Europe producing over 400 products on a continuous flow production line. The insulation products can contain added features, such as fabric or aluminum adhered to one side, multiple densities, or wire woven into the product.

Qualitative data on the production process, production scheduling process and scheduling rules, and product features was gathered from the ERP system, product specification sheets, and semi-structured interviews with the following factory personnel: 1 manager, 1 process engineer, 4 product managers, 1 IT specialist, 2 production planners, 4 operators, and 1 quality manager. All personnel were interviewed once for 45 minutes, except for the factory manager and process engineer who were interviewed 4 times for 45 minutes. Eighteen candidates for independent variables affecting production throughput were identified through the interviews. Variables were separated into product and process variables in Tables 1 and 2, respectively.

<table>
<thead>
<tr>
<th>Product / Process variable</th>
<th>Description of variable</th>
<th>Data Type</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td>Structural parameter</td>
<td>Discrete</td>
<td>ERP</td>
</tr>
<tr>
<td>Height</td>
<td>Dimension</td>
<td>Discrete</td>
<td>ERP</td>
</tr>
<tr>
<td>Lambda</td>
<td>Thermal conductivity coefficient</td>
<td>Discrete</td>
<td>ERP</td>
</tr>
<tr>
<td>% Binder Content</td>
<td>Recipe parameter</td>
<td>Discrete</td>
<td>ERP</td>
</tr>
<tr>
<td>Fleece</td>
<td>Fabric applied to one side of product</td>
<td>Binary</td>
<td>Spec. sheet</td>
</tr>
<tr>
<td>Dual Density</td>
<td>1 if product has two densities, 0 otherwise</td>
<td>Binary</td>
<td>Spec. sheet</td>
</tr>
<tr>
<td>Galvanized Steel Mesh</td>
<td>Wire woven into product</td>
<td>Binary</td>
<td>Spec. sheet</td>
</tr>
<tr>
<td>Stainless Steel Mesh</td>
<td>Wire woven into product</td>
<td>Binary</td>
<td>Spec. sheet</td>
</tr>
<tr>
<td>Aluminum Foil</td>
<td>Foil applied to one side of product</td>
<td>Binary</td>
<td>Spec. sheet</td>
</tr>
<tr>
<td>Length</td>
<td>Dimension</td>
<td>Discrete</td>
<td>ERP</td>
</tr>
<tr>
<td>Width</td>
<td>Dimension</td>
<td>Discrete</td>
<td>ERP</td>
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Table 2. Process independent variables

<table>
<thead>
<tr>
<th>Product / Process variable</th>
<th>Description of variable</th>
<th>Data Type</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sequence</td>
<td>Indicates if runs are sequenced to minimize changeover waste</td>
<td>Binary</td>
<td>MES, Interviews</td>
</tr>
<tr>
<td>Run length</td>
<td>Run time excluding planned/unplanned stop orders</td>
<td>Continuous</td>
<td>MES</td>
</tr>
<tr>
<td>Double Batch</td>
<td>Indicates if product is the same as product in previous run</td>
<td>Binary</td>
<td>MES</td>
</tr>
<tr>
<td>Crew 1</td>
<td>Indicates crew 1</td>
<td>Binary</td>
<td>MES, Interviews</td>
</tr>
<tr>
<td>Crew 2</td>
<td>Indicates crew 2</td>
<td>Binary</td>
<td>MES, Interviews</td>
</tr>
<tr>
<td>Crew 3</td>
<td>Indicates crew 3</td>
<td>Binary</td>
<td>MES, Interviews</td>
</tr>
<tr>
<td>Crew 4</td>
<td>Indicates crew 4</td>
<td>Binary</td>
<td>MES, Interviews</td>
</tr>
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</table>
Production run data from the manufacturing execution system (MES) for 2016 was the primary dataset. Data was cleaned of infeasible values due to data entry error (e.g. run length under 5 minutes), production stops, and outliers with an assignable cause (e.g. scrap over 20% of gross production). Since throughput of the line is determined by the bottleneck machine for each product, MES data was segmented by bottleneck groups.

Nine linear models, one per bottleneck group, were constructed using the 18 independent variables and dependent variable, production throughput. Models were solved using lasso regression to handle the high number of variables and potential multicollinearity [5]. The cost-function penalization parameter $\lambda$ was found using inner, k-fold cross-validation where $k = 20$ for each bottleneck group model.

Preliminary results show that product features partially impact throughput. For example, adding aluminum foil to a product in bottleneck group 9 reduces throughput by 6%. In contrast, fleece is considered “free” variety since throughput does not reduce significantly for fleece products. Run length and sequence show the largest impact on throughput. This research will further develop to refine the model and recommend variety management initiatives.

References

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Why slow down? Factors affecting speed loss in process manufacturing

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* Corresponding author

Abstract: Loss of production speed is an unavoidable reality for process manufacturers. Reduced production speeds are shown to consume 9%–15% of available production capacity in various production contexts and create substantial costs for capital-intensive process industries. Among the least-examined of Nakajima’s (1988) six big efficiency losses measured within total product maintenance, speed loss presents significant opportunities for potential efficiency improvements in manufacturing companies. This paper presents an overview of the factors related to speed loss based on the literature and uses a case study of two production lines to quantify the scale of speed loss for the factors identified in the case study. For quantification, generalised least squares regression is performed to study the relationship between each factor and speed loss. The analysis of the production data reveals that technology and management-related factors have the strongest correlations with speed losses in this industry and account for the most speed loss. This research can directly support operational improvement initiatives in practice by identifying the factors with the strongest relationships to speed loss, aiding practitioners to select the most relevant means to improve speed and identify appropriate overall equipment effectiveness targets.

Keywords: Speed Loss, TPM, OEE, Productivity, Process Industry
Introduction

Speed loss is an expensive, technical reality for large-scale, complex production processes. Formally identified as a source of lost capacity by Nakajima (1988) in the total productive maintenance (TPM) methodology, speed loss is any deviation from the designed production speed or throughput in a manufacturing context caused by rough running, equipment wear, tool wear and operator inefficiency, among other factors (Tsarouhas 2007). Running at reduced speed can silently reduce the capacity of production lines, reducing service levels in capacity-constrained situations and eroding efficiencies in situations of surplus capacity. Reduced production speeds are shown to consume 9%–15% of available capacity in cases in the literature (Ljungberg 1998; Ahmed, Hj. Hassan, and Taha 2004) and reduced capacity from reduced production speeds thought to be higher in the large, automated production and packaging systems characteristic of process manufacturing (Ljungberg 1998; Nakajima 1989). For large-scale process lines with millions of euros of revenue, increasing speed efficiency in production by only 1% can give firms competitive cost advantages over other players in the market (Zuashkiani, Rahmandad, and Jardine 2011).

Capacity losses due to reduced speed, though, are often overlooked by management and are not prioritised due to a mindset seeing some speed loss as allowable and to the difficulty of eliminating speed loss (Jonsson and Lesshammar 1999; Benjamin, Marathamuthu, and Murugaiah 2015). Factory management and maintenance departments tend to focus on the more pressing demands of large production stop times than the smaller, persistent losses from variations in run rate (Ljungberg 1998; Benjamin, Marathamuthu and Murugaiah 2015). Speed loss is also difficult to notice in production as familiarity with the process can hinder operators’ ability to detect deviations in speed (Benjamin, Marathamuthu and Murugaiah 2015), and unambitious speed targets keep factories from achieving their maximum potential speed.

Many companies have not been able to calculate the precise magnitude of speed loss due to poor data registration (Hedman, Subramaniyan and Almström 2016; Ahmed, Hassan and Taha 2004; Ljungberg 1998). Difficulties in data collection partly stem from the chronic nature of speed loss as a production disturbance. Unlike sporadic disturbances easily recognisable as large deviations from the normal state, chronic disturbances are usually small, numerous, hidden and complicated, have many concurrent causes and are often regarded as normal (Ljungberg 1997).

Considering the chronic nature of speed loss and the difficulties addressing its causes, the operations management and TPM literature lacks solutions specifically addressing speed loss (Benjamin, Marathamuthu and Murugaiah 2015). Furthermore, the TPM literature includes limited quantification of speed loss and even less work guiding the identification of factors and quantifying factors’ relative effects, particularly for process industry manufacturers (e.g. producers of food, oil, gas, chemical, metals, and commodity materials). Lastly, there is no discussion on the possibility of minimum expected speed losses for different operations based on the process technology, process variability and other factors unique to individual production settings. This information could aid operations managers in driving improvement initiatives, helping them discern potential speed improvements that could be realised through standardisation, capital expenditures and technological advancements.

This article contributes to the TPM and operations management literature with a study examining speed loss figures for two process lines, a measure often unquantified in overall equipment effectiveness (OEE) studies due to the difficulty of data collection. Additionally, the study examines the mechanical underpinnings of speed loss on process manufacturing equipment, the factors that may impact this speed loss and the relative effects of each identified factor. To the best of the researchers’ knowledge, this study presents the first
comprehensive examination of possible factors leading to speed loss and the first application of regression analysis to quantify speed loss related to each factor in a case of two production lines.

Two research questions (RQ) are used to guide this investigation of speed loss:

1. What factors affecting speed loss are identified in the literature?
2. Based on a case study, which of these factors are relevant to a process manufacturing line?

The study is structured as follows. First, a review of the literature discussing OEE, speed loss and factors related to speed loss is presented. Next, the mixed-methods research design employing qualitative, thematic analysis and quantitative regression analysis is described, and the case company is introduced. The factors identified in the case study are presented and used to build a generalised least squares (GLS) regression model, which is interpreted and discussed. Strong evidence supporting associations of speed loss with (1) technological constraints and (2) factors under management’s influence is identified. Finally, conclusions are drawn, and avenues for future work are presented.

Relevant literature

**Speed loss and overall equipment effectiveness**

The use of speed loss as an operational performance measure has its roots in TPM, a methodology to maintain and improve equipment performance in manufacturing organisations developed by Nakajima (1988). The TPM methodology focuses on three main areas: maximisation of equipment effectiveness, operators’ autonomous maintenance of equipment and the use of small group activities (Nakajima 1989; Dal, Tugwell and Greatbanks 2000). OEE is defined as a measure of ‘the ability to run equipment without failure, at the designed speed and with zero defects’ (Muchiri and Pintelon 2008, 3528) and is primarily used to prioritise efficiency improvements in manufacturing (Jonsson and Lesshammar 1999).

To maximise equipment effectiveness, Nakajima (1988) defines six big losses in OEE that should be quantified and reduced. The six big losses are subdivided into three categories as follows:

**Availability losses (A)**
1. Equipment breakdown, causing reduced productivity or waste in defective products
2. Setup and adjustment losses

**Performance losses (P)**
3. Idling and minor stops due to interruptions or temporary malfunction
4. Speed loss from reduced run rates, measured as the difference between the equipment’s designed speed and operating speed

**Quality losses (Q)**
5. Defects and rework
6. Start-up losses occurring in an early stage of production

OEE is calculated as shown in equations 1–4 based on the method proposed by Nakajima (1988). Equation 3 for performance efficiency is written in an expanded form to reveal the two sub-calculations: (1) the ratio of production speeds; and (2) the calculation of small stops’ impacts (Dal, Tugwell and Greatbanks 2000; de Ron and Rooda 2006). The ratio
of production speeds can be expressed as speed efficiency (equation 5), whose complement is speed loss (equation 6).

\[
AE = \frac{Total\ time - Unplanned\ downtime}{Ideal\ cycle\ time} 
\]

\[
PE = \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} \times \frac{Actual\ cycle\ time \times Output}{Operating\ time} 
\]

\[
QE = \frac{Output - Quality\ defects}{Output} 
\]

\[
OEE = AE \times PE \times QE 
\]

\[
Speed\ efficiency = \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} 
\]

\[
Speed\ loss = 1 - \frac{Ideal\ cycle\ time}{Actual\ cycle\ time} 
\]

where,

- **Total time** = Operational time of equipment, excluding planned stops for holidays, maintenance and lack of orders
- **Unplanned downtime** = Time when equipment is scheduled for production but is unable to produce
- **Ideal cycle time** = Average theoretical processing rate of equipment for a given product mix
- **Actual cycle time** = Weighted average processing rate for equipment with a given product mix
- **Output** = Gross output of material produced by the equipment
- **Quality defects** = Material rejected for not passing quality inspections

Nakajima (1988) defines world-class performance in the OEE subcategories as availability efficiency (AE) of more than 90%, performance efficiency (PE) of more than 95% and quality efficiency (QE) of more than 99%, with the three measures multiplied to a world-class OEE of 84%. However, good OEE performance is argued to be industry-specific as OEE is influenced by external factors, such as material handling systems and inventory buffers (Chan et al. 2005; de Ron and Rooda 2006; Hedman, Subramaniyan and Almström 2016). For example, in a study of 23 companies, food and beverage companies are found to have a higher median OEE (74%) than other types of companies, while automated discrete production companies have the lowest OEE (59%) (Hedman, Subramaniyan and Almström 2016).
**Previous speed loss studies**

Whereas the magnitude of lost PE is known to be large, the magnitude of speed loss (and its complement, speed efficiency) is not directly calculated in many papers. Table 1 displays the PE of the case studies identified in the literature, with speed efficiency calculated in only two of the eight articles. PE varies from 54% to 100% across the studied cases, with speed loss of 85% and 91% in the two cases identified.

**Table 1. Performance loss in OEE case studies detailing performance efficiency**

<table>
<thead>
<tr>
<th>Author</th>
<th>Company</th>
<th>Performance efficiency</th>
<th>Speed efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahmad, Hossen and Ali (2018)</td>
<td>Yarn producer, single process</td>
<td>80%–89%</td>
<td>85%–91%</td>
</tr>
<tr>
<td>Dal, Tugwell and Greathans (2000)</td>
<td>Airbag producer, weaving department</td>
<td>85%</td>
<td>N/A</td>
</tr>
<tr>
<td>Hedman, Subramaniyan and Almström(2016)</td>
<td>23 companies (seven food/beverage plants, nine mechanical workshops, four discrete automated plants, three polymeric plants)</td>
<td>100% for 80% of companies</td>
<td>N/A</td>
</tr>
<tr>
<td>Jonsson and Lesshammar (1999)</td>
<td>Construction vehicle producer, metal profiles manufacturer</td>
<td>85%–94%</td>
<td>N/A</td>
</tr>
<tr>
<td>Ljunberg (1998)</td>
<td>23 machinery systems</td>
<td>68%</td>
<td>91%</td>
</tr>
<tr>
<td>Ohunakin and Leramo (2012)</td>
<td>Beverage bottling facility</td>
<td>54%–65%</td>
<td>N/A</td>
</tr>
<tr>
<td>Tsarouhas (2007)</td>
<td>Pizza production line</td>
<td>80%–97%</td>
<td>N/A</td>
</tr>
<tr>
<td>Tsarouhas (2013)</td>
<td>Italian cheese production line</td>
<td>87%</td>
<td>N/A</td>
</tr>
</tbody>
</table>

**Factors related to speed loss**

Researchers and practitioners cite several reasons for reduced operating speed on manufacturing lines, including factors related to process technology, factory management, materials and quality, among other aspects (see Table 2). By design, the characteristics of process technology influence production speed. Mechanical and electrical issues, old age and high wear can cause machines to run below the ideal cycle time while operating (Nakajima 1988; Tsarouhas 2007). Unplanned maintenance stops are also known to affect speed loss as time is needed to bring production back to normal speed after unplanned stops (Zuashkiani, Rahmandad and Jardine 2011). While physical limitations are considered in determining the ideal cycle times for machines in the engineering stage, machinery may operate at less than ideal capacity due to further technological constraints (e.g. downstream bottlenecks) and environmental limitations placed on factories (Ogle and Carpenter 2014). Depending on the technology, there might also be a natural level of variation in the speeds of machines (Anderson and Sedatele 2012).

Differences in crew, work standards, performance targets and the management of operators are also known sources of variations in production speed (Hopp and Spearman 2008) and are directly controllable by factory management. Beyond production, a lack of standard operating procedures for maintenance activities can contribute to technical issues, such as equipment malfunction, forcing operators to reduce production speed (Nakajima 1988). A further factor within management’s discretion is the determination of ideal cycle
times and speeds for equipment if no ideal cycle times are given in the equipment specifications. In industrial applications of OEE, speed loss is found to be negative in certain instances, implying that ideal speeds are often set too low for certain processes (Ljungberg 1998).

Production scheduling and sequencing, often under the influence of factory management, are shown to be significant factors affecting speed variations in production (Berry and Cooper 1999; Anderson and Sedatole 2012). When producing multiple product variants with different ideal speeds and sequence-dependent setup times, it is critical that the products be sequenced to avoid large shifts in production speed and long stops for setup (Anderson and Sedatole 2012).

Table 2. Publications discussing factors affecting loss of production speed in manufacturing contexts

<table>
<thead>
<tr>
<th>Speed loss factors</th>
<th>Publications discussing factors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Technology</strong></td>
<td></td>
</tr>
<tr>
<td>Equipment age and wear</td>
<td>Nakajima (1988), Benjamin, Marathamuthu and Murugaiah (2015)</td>
</tr>
<tr>
<td>Natural process variation</td>
<td>Anderson and Sedatole (2012)</td>
</tr>
<tr>
<td>Queue capacity for work in process</td>
<td>Aboutaleb et al. (2017)</td>
</tr>
<tr>
<td><strong>Factory management</strong></td>
<td></td>
</tr>
<tr>
<td>Production scheduling</td>
<td>Berry and Cooper (1999), Anderson and Sedatole (2012), Allwood et al. (2015), Aboutaleb et al. (2017)</td>
</tr>
<tr>
<td><strong>Materials</strong></td>
<td></td>
</tr>
<tr>
<td>Raw material mix</td>
<td>SEMI (2014)</td>
</tr>
<tr>
<td><strong>Quality (finished goods)</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Other</strong></td>
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</table>
Speed on production lines may also be reduced to prevent products from being rejected in quality inspections (Nakajima 1988). Nurani and Akella (1992) identify an inverted U-shaped relationship between production speed and profit accrual rate: at very high levels of speed, profits decrease due to higher quality-related expenses (e.g. scrap costs and opportunity costs of lost sales). Determining the maximum production speed that does not reduce product quality, therefore, is of interest when managing speed loss.

Other factors, such as capacity utilisation and product variety, are also shown to be related to the loss of production speed or throughput. The number of product variants sold by firms is shown to grow as firms globalise, expand markets and expand capacity (Allwood et al. 2015; Fisher and Ittner 1999). If not properly managed, product variety can decrease production speeds as low-volume products increase the number of changeovers and destabilise process settings (Berry and Cooper 1999; Fisher and Ittner 1999; Allwood et al. 2015; Nakajima 1988). Similarly, the utilisation of machines determines the degree to which they can operate at ideal speed. Capacity-constrained machines are commonly pressed to operate closer to the ideal production speed than machines with excess capacity, as in the case of an OEE study by Ljungberg (1998).

**Methods for quantifying the effects of speed loss factors**

Improvement methodologies in the lean and TPM toolboxes are used to address speed loss in the literature (Benjamin, Marathamuthu and Murugaiah 2015; Nakajima 1988), but the methodologies are few and have limited explanatory and statistical power. First, Nakajima (1988) proposes a four-step method to set progressively higher speed targets and reduce speed loss:

1. Achieve the standard speed for each product.
2. Increase the standard speed for each product.
3. Achieve the designed speed.
4. Surpass the designed speed.

This approach is designed to expose hidden problems, such as inadequate maintenance, inappropriate setup and tuning and improper testing in the equipment design phase, among others (Nakajima 1988). However, the method offers little guidance on how to isolate and quantify the speed loss arising from specific factors.

Second, Benjamin, Marathamuthu and Murugaiah (2015) take an explanatory approach applying the 5 Whys technique to assess speed loss at a metal barrel manufacturer. Benjamin, Marathamuthu and Murugaiah (2015) apply Pareto analysis to speed loss issues and perform the 5 Whys method with the most commonly occurring issues to identify and address the cause. While identifying reduction in speed loss equalling 32,000 USD at the case company (Benjamin, Marathamuthu and Murugaiah 2015), the approach gives only rudimentary consideration to speed loss from different factors, examining each factor in isolation instead of assessing the factors’ collective, incremental impact on speed loss. Furthermore, the 5 Whys approach is not ideal for assessing process manufacturing systems, which have many interacting sources of speed variation and many parameters to consider when increasing speed.

**Methodology**

A mixed-methods approach incorporating case study research and quantitative analysis is utilised to investigate the research questions. The case study method is appropriate for studies with unclear boundaries between the phenomenon and the context (Yin 2018). This research is aimed at identifying factors related to speed loss in process manufacturing firms and
quantifying their relationship, so the case study approach is appropriate. Archival analysis of production data is also utilised.

First, a rigorous qualitative, thematic analysis of written operator input is performed to identify possible factors influencing speed reductions at the case company. This is followed by regression analysis of production data to quantify the magnitude of the relationship of speed loss with each identified factor. This mixed-methods approach is classified as an exploratory sequential mixed-methods approach, in which qualitative analysis feeds the collection and analysis of quantitative data from which conclusions are drawn (Creswell 2014). In the following sections, the case company is introduced, and the thematic and quantitative analysis approaches are detailed.

**Background of the case company: InsCo**

The case company selected for analysis is a building insulation production facility in Europe, hereafter referred to as InsCo. InsCo is selected as it utilises a high-volume, continuous-flow process representative of the process industry. The factory consists of two production lines with similar layouts and product mixes. Both lines operate 24 hours a day, seven days a week, with a four-crew, rotating work schedule. The managers and personnel operating both lines are well acquainted with lean tools and recently implemented OEE to measure production losses on the two lines. The lines have not experienced any major changes in capacity utilisation, production technology or product mix in the past five years, making them favourable for analysis. Both lines are assessed in this study and are referred to as L1 and L2 throughout the paper.

The insulation production process (see Figure 1) consists of a hot end where a combination of raw materials is melted and spun into fibres. The fibres are combined with recycled fibres from downstream waste, creating the primary material, which is compressed into a final form before being cured, cooled, cut and packed per product specifications. The continuous, circular nature of InsCo’s production process is characteristic of process manufacturing (Ogle and Carpenter 2014).

**Figure 1. Insulation production process**

Among the measures of speed or throughput on the production line, the primary material throughput (i.e. primary speed) is used to measure speed in this study. Primary speed is selected as it is a directly controllable speed upstream in the process, and live data on primary speed are immediately relayed to operators through process control visuals. Downstream speed measures are not favourable for analysis as they are subject to many additional sources of variation, including manual data registration. Primary speed can be adjusted by melting and spinning more fibres or adding more recycled fibres. Increasing the output of the spinning process must be done gradually given the technological limitations and
environmental constraints. The recycled material content can be increased almost instantaneously if recycled fibres are present in the system.

Each production batch represents a single product variant, which is a unique combination of mechanical and thermal properties, dimensions and packaging materials. Changes between batches of different products can occur during production stops and runtime with non-conforming products rejected from the line as waste. Primary speed thus encompasses production of non-conforming material rejected downstream.

In the spring of 2016, InsCo implemented a speed standardisation programme. Lacking official, ideal cycle times for product variants, factory management set maximum speed targets for the primary speed for each product based on performance in the previous year. The targets are incorporated into a visual control tool: a digital speedometer (see Figure 2), indicating whether the operators are on target (green), slightly under target (yellow) or far under target (red). If the target primary speed is not achieved for a given production batch, the operators enter an explanation into a free text field in the manufacturing execution system (MES).

Examining the target primary speed compared to the actual primary speed reveals that L1 and L2 often exceed the speed targets set by management (see, e.g., Figure 3), creating negative speed loss. The highest demonstrated, sustainable primary speed for each product is used as the ideal speed to avoid negative speed loss in the quantitative study (Ogle and Carpenter 2014). To determine the highest demonstrated, sustainable primary speed, the researchers assess batches within the technical capabilities of the processes demonstrated in the period analysed and sustainable for a batch of greater duration than 30 minutes. If no feasible primary speed is found for a product in the period analysed, the factory target primary speed is used.

Both the qualitative and quantitative analyses are performed using three months of data at InsCo from 1 November 2017 to 31 January 2018, a stable period of operations at the company when the use of the speed tool was well established in the organisation.

---

**Figure 2. Speedometer used to monitor primary speed-target status at InsCo (conceptual)**
Thematic analysis of possible factors

Data on suspected causes of speed loss from the operators’ perspective were extracted at the batch level from the MES, translated from the local language into English using Google Translate software and coded by the researchers (Google 2018). Translated meanings unclear to the researchers were verified with the factory manager. A preliminary set of speed loss causes was presented to the factory manager, whose feedback was incorporated to consolidate the factors. Three 1-hour, semi-structured interviews with the factory manager were held to understand the production context, scope the analysis and report the results. These discussions focused on the format of the speed variance tool, structure of the data, use of the tool and factors likely to affect speed loss at the factory.

General linear regression

Data for the speed loss factors from the thematic analysis were compiled from various sources at the case company to inform the quantitative study. Sensor data on the primary speed and recycled material speed were collected from the production data warehouse and pre-processed in the statistical software program R, using a local regression to create smooth curves and eliminate signal noise while fitting the predominant trends in the process variables. The data were cleaned of production stop times (primary speed of 0 tons per hour) to assess only equipment uptime. Outliers for the primary speed, classified using 1.5 times the interquartile range of the signal, were removed from the dataset. Sensor data from every
30 minutes of production time were analysed to capture the dynamic nature of production activities not visible at higher levels of aggregation (Anderson and Sedatole 2012).

Batch-level data containing the coded operator data, primary speed targets, and downtime information were also extracted and mapped to the sensor data. The analysis included a total of 1,231 production batches for 600 products from L1 and 626 batches of 300 products from L2. Additional data used in the analysis were the crew schedule and maintenance data from Excel spreadsheets at the factory.

The maximum likelihood estimates of regression coefficients for the combined factors were calculated using GLS regression using the nlme package in R (R Core Team 2018; Pinheiro et al. 2018). Regression analysis is proven to be an appropriate method for analysing changes in throughput and costs in chemical and glass producers (Berry and Cooper 1999; Anderson and Sedatole 2012). General linear regression is specifically applicable to regressing on time-series data due to serial correlations and heteroskedasticity in error terms (Wooldridge 2006).

In the following discussion of the findings, statistically significant factors are evaluated from a mechanical perspective to determine if the correlations evaluated in the regression analysis are causal. Although a significant correlation coefficient in a regression cannot be taken as direct evidence of a causal relationship between the factors and speed loss (Wooldridge 2006), the combination of a significant correlation coefficient and a mechanical explanation of a relationship can paint a stronger picture of causality.

Findings

Current speed loss at InsCo

The OEE for L1 and L2 for the period studied are assessed using the method described by Nakajima (1988), and the results are summarised in Table 3. The data registration practices at the firm allow recording all production stops, small and large, as unplanned downtime, moving the effect of small stops from the PE measure to the AE measure. Consequently, PE measures speed loss in isolation.

Table 3 shows that QE is the lowest of the OEE sub-measures at InsCo. The second lowest sub-measure is PE in the form of lost speed efficiency, equating to 9%–10% of lost capacity at InsCo. AE for both lines is higher than 90% and reaches the world-class standard within the TPM literature (Nakajima 1988).

Identifying factors related to speed loss

Nine main groups of speed loss causes are identified through a thematic review of operator input to the MES through the speed tool. Figure 4 shows the frequency distribution of the cited causes of speed loss on the two lines over the three-month period. The analysis is restricted to runs when InsCo’s speed loss target is not achieved. More than one speed loss...
cause may be cited for a single batch. The most frequently cited causes of speed loss are furnace limitations (e.g. approaching a furnace’s maximum capacity and approaching environmental limits on emissions) and draining of by-products created during melting from the furnace. Also cited are reduced speeds due to production planning (e.g. short run duration and large shifts between product speeds), production stops, raw material issues, lack of recycling material, start-up of the line, technical issues with equipment and quality issues experienced at the end of the line.

Interview data from factory management and process experts enable identifying additional possible causes of speed loss, including crew differences, product variety, factory learning curve, recycled content and natural process variation. These variables and those in Figure 4 are aggregated, and the impact on speed loss is assessed in the following section.

![Figure 4. Distribution of operator-suspected causes of speed loss](image)

**Quantifying the relationships between the factors and speed loss**

A GLS regression model is constructed using the aggregated set of variables to reveal the potential causal relationships between the factors and speed loss at InsCo. Equation 7 shows the dependent variable measured as the percentage speed loss based on the defined target speed for each product. Speed loss is expressed in percentage form to normalise the differing primary speed targets for the various products.

\[
SPLOSS_i = \frac{(Target_i - Actual)}{Target_i} \times 100
\]  

(7)

The independent variables (defined in Table 4) are assessed for multicollinearity using Pearson’s correlation coefficients (for the results, see appendices 1 and 2 for L1 and L2, respectively). Correlations close to 0.5 are identified among the crew variables for both L1 and L2. The correlation coefficients for the crew variables do not significantly exceed 0.5, so the crew variables are included in other stages of the modelling. The two production lines are assessed individually as it is hypothesised that the significance of different factors varies across the two lines.
### Table 4. Independent variable definitions

<table>
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<tr>
<th>Variables</th>
<th>Description</th>
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<tbody>
<tr>
<td><strong>RUNTIME</strong></td>
<td>Hours of uptime for the current batch, mean centred to 0</td>
</tr>
<tr>
<td><strong>PREVSP</strong></td>
<td>Percentage change in the target speed of the current batch and the target speed of the previous batch, mean centred to 0</td>
</tr>
<tr>
<td><strong>NEXTSP</strong></td>
<td>Percentage change in the target speed of the current batch and the target speed of the following batch, mean centred to 0</td>
</tr>
<tr>
<td><strong>FURN</strong></td>
<td>1 if the current batch has a furnace limitation cited by the operators; 0 otherwise</td>
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<tr>
<td><strong>TECH</strong></td>
<td>1 if the current batch has a technical issue cited by the operators; 0 otherwise</td>
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<tr>
<td><strong>PRSTOP</strong></td>
<td>1 if the current batch has a production stop per the MES data; 0 otherwise</td>
</tr>
<tr>
<td><strong>QUAL</strong></td>
<td>1 if the current batch has a quality issue cited by the operators; 0 otherwise</td>
</tr>
<tr>
<td><strong>RECYC</strong></td>
<td>Recycling fibres in tons per hour from smoothened sensor data, mean centred to 0 and scaled using standard deviation.</td>
</tr>
<tr>
<td><strong>RAWMAT</strong></td>
<td>Tons of raw material per hour added to the melting process from smoothened sensor data, mean centred to 0 and scaled using standard deviations</td>
</tr>
<tr>
<td><strong>BYPROD</strong></td>
<td>1 if a by-product is drained from the furnace during run time; 0 otherwise</td>
</tr>
<tr>
<td><strong>MATER</strong></td>
<td>1 if the current batch has a material issue cited by the operators; 0 otherwise</td>
</tr>
<tr>
<td><strong>LEARN</strong></td>
<td>A continuous variable measuring the number of days since 1 November 2017, the beginning of the analysis period</td>
</tr>
<tr>
<td><strong>CREW1</strong></td>
<td>1 if the current batch is produced by the crew 1; 0 otherwise</td>
</tr>
<tr>
<td><strong>CREW2</strong></td>
<td>1 if the current batch is produced by the crew 2; 0 otherwise</td>
</tr>
<tr>
<td><strong>CREW3</strong></td>
<td>1 if the current batch is produced by the crew 3; 0 otherwise</td>
</tr>
</tbody>
</table>

A parsimonious array of 15 variables is assessed based on the qualitative speed loss causes cited by the operators and the feedback from management given in the interviews. Exploratory, univariate analysis reveals that all fifteen variables are suitable for modelling with a linear relationship to percentage speed loss. There are no suspected interaction effects among the variables, so variable interactions are omitted from the model. The final model tested using GLS regression is shown in equation 8. Crew four is selected randomly as the base crew to which the other crews are compared in the model, so the crew four variable is excluded from equation 7.

\[
SPLOSS_t = \beta_0 + \beta_1 RUNTIME_t + \beta_2 NEXTSP_t + \beta_3 PREVSP_t + \beta_4 FURN_t + \beta_5 TECH_t + \beta_6 PRSTOP_t + \beta_7 QUAL_t + \beta_8 BYPROD_t + \beta_9 MATER_t + \beta_{10} LEARN_t + \beta_{11} RECYC_t + \beta_{12} RAWMAT_t + \beta_{13} CREW1_t + \beta_{14} CREW2_t + \beta_{15} CREW3_t + \epsilon_t
\]
Table 5. Maximum likelihood estimates for the relationships between the process variables and the percentage speed loss on the two lines, L1 and L2, using GLS regression.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>T value</th>
<th>P value</th>
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<td>Intercept</td>
<td>-0.204</td>
<td>0.38563</td>
<td>-0.539</td>
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<td>RUNTIME</td>
<td>0.047</td>
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<td>0.101</td>
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<td>PREVSP</td>
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<td>0.012</td>
<td>14.714</td>
<td>0.000</td>
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<td>FURN</td>
<td>2.684</td>
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<td>12.934</td>
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<td>0.219</td>
<td>0.022</td>
<td>0.983</td>
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<tr>
<td>PRSTOP</td>
<td>-0.232</td>
<td>0.430</td>
<td>-0.540</td>
<td>0.589</td>
</tr>
<tr>
<td>QUAL</td>
<td>0.431</td>
<td>0.238</td>
<td>1.814</td>
<td>0.069</td>
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<tr>
<td>RECYC</td>
<td>-2.444</td>
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<td>-27.705</td>
<td>0.000</td>
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<tr>
<td>RAWMAT</td>
<td>-1.694</td>
<td>0.083</td>
<td>-20.238</td>
<td>0.000</td>
</tr>
<tr>
<td>LEARN</td>
<td>-0.028</td>
<td>0.003</td>
<td>-9.142</td>
<td>0.000</td>
</tr>
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<td>CREW1</td>
<td>0.598</td>
<td>0.236</td>
<td>2.529</td>
<td>0.012</td>
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<tr>
<td>CREW2</td>
<td>1.179</td>
<td>0.236</td>
<td>5.000</td>
<td>0.000</td>
</tr>
<tr>
<td>CREW3</td>
<td>1.639</td>
<td>0.241</td>
<td>6.799</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Res. st. error = 4.369, degrees of freedom = 2965

Pseudo $R^2 = 0.665$

Significance codes: (.) p < 0.1, (*) p < 0.05, ** p < 0.01, *** p < 0.001

and L2 using GLS regression for the relationships between the process variables and the percentage speed loss on the two lines, L1 and L2, using GLS regression.
The GLS regression results are shown in Table 5 for L1 and L2. For both models, the intercept is positive and significant, but the intercept is not shown for confidentiality. The variables that have statistically significant correlations with speed loss include the learning curve, select crew variables, batch runtime, percentage change in target speed between consecutive batches, limitations of the melting furnace and draining of by-products from the furnace. Quality issues with finished goods are significant only in the L1 model, while technical issues are significant in the L2 model.

The researchers expect higher RUNTIME to be associated with decreased speed loss, but the results show this is true only for L2. In L1, longer run times are related with increased speed loss. One potential underlying cause is that average runtimes in L1 are half of L2. For both models, the runtime coefficient is not large and explains no more than 1%–2% of the change in speed loss based on typical run times at InsCo.

Both variables measuring the percentage change in speed targets for subsequent batches are significant. During operation, operators are known to anticipate higher speed later in the schedule and pre-emptively increase speed to prepare for the coming fast product. Evidence for this behaviour can be seen in the negative coefficient for NEXTSP, which reveals that if the next product to be produced on L1 or L2 has a higher primary speed target than the current product being processed, speed loss for the current product decreases. When assessing the effect of the previous product, the positive coefficient for PREVSP shows that if the previous product has a lower primary speed target than the current product being processed, speed loss for the current product increases (i.e. the line runs slower). In other words, it is preferable to schedule a product with high speed loss either after a faster product or before a faster product to avoid lost speed.

The batch runtime and the change in target speed between batches are largely determined by the production planning department. Although planners optimise the batch size and production sequence using experience-based heuristics, the production plan is still subject to last-minute schedule changes, which can cause large changes in speed. Primary speed can be adjusted quite quickly using recycled material, but if recycled material is not present, or if the maximum amount of recycled material for a product is already administered, then the furnace output must be adjusted at a very slow rate, which can cause a slower line speed at the beginning of a batch.

The quality of the finished product at the end of the line is also a statistically significant factor related to increased speed loss on L1. Quality issues are cited by the operators as a cause for decreased speed performance in 14% of all runtime on L1 and 11% of all runtime on L2. In case of poor quality, operators controlling primary speed receive feedback from the testing and inspection department on whether products’ physical and aesthetics specifications are met. In some cases, corrective action is taken to reduce the line speed. Speed loss due to poor quality is estimated in 0.4% for the L1 model. The quality variable in the L2 model has a similar magnitude and direction as the L1 model, with a positive coefficient, but is only slightly statistically significant when considering the other variables.

Technical issues on the line (e.g. machine breakdown and reduced capacity) are significantly related to a 1% increase in speed loss only in the L2 model. The reason for the lack of significance of TECH in L1 is interesting as there are no noticeable differences in runtime affected by technical issues on L1 and L2. Further context was provided from the factory manager who explained in an interview that L2 suffered from higher severity mechanical failures in the period studied than L1, being a possible explanation for the significance of TECH on L2 and not L1.

The variables with the most negative impact on speed loss (positive coefficients) are by-product drain and furnace limitations. Draining by-products from the furnace is an
obligatory task operators perform periodically to fulfil product specifications and factory safety procedures. By-products are drained from the furnace during approximately 4% of all runtime on both L1 and L2 in the period analysed. The impact of by-product draining is more drastic on L2, related to a 7% speed loss on but a 4% capacity loss on L1. Similarly, furnace limitations are related to an additional 2%–3% speed loss on L1 and L2 based on the model coefficients. This loss is sizeable considering that operators cite furnace limits for 25% and 47% of the runtime on L1 and L2, respectively. Multiplying the coefficients by the frequency of occurrence of FURN in the data, the variable FURN alone is related to an average 0.7% speed loss on L1 and 1% speed loss on L2.

Raw materials and recycling have negative, statistically significant coefficients in both models, indicating that additional flow of material from upstream allows operators to better achieve speed targets. A lack of recycling has dramatic effects on the speed loss on the production line and is cited as a cause of speed loss in 5% of batches on L1.

The variables for crews 1–3 indicate statistically significant differences from the performance of the control crew (crew 4) on both lines. The positive coefficients for all crew variables in both models suggest that crew 4 performs with the lowest speed loss on both lines.

An additional variable with a negative, significant regression coefficient in both models is the learning curve variable. The results show that for each additional day of experience operators on L1 and L2 have, the percentage speed loss on the line decreases by nearly one-fortieth of a percentage point, or one percentage point in forty days. The factory manager confirms that his team focused on speed loss activities on both lines in the period examined.

Variables with no significant relationship with percentage speed loss are production stops and raw material issues (e.g. material availability and quality). These variables are expected to relate to increased speed loss as they interrupt flow, but this is not the case.

Discussion and Conclusions

This in-depth study of speed loss on two process manufacturing lines reveals that many significant factors related to speed loss are embedded in production technology and process control (e.g. raw material dosing, furnace limitations and the presence of recycling). The factors identified are related to the process design and technology installed at the factory, variables over which operators have little influence in daily operations. Instead, engineering resources are needed to better understand and mitigate furnace limitations, by-product draining and raw material and recycling dosing, which are related to speed loss.

The results of the analysis highlight specific sources of variation in production speed at InsCo, helping factory management to identify logical means to address these sources. Addressing furnace limitations is a key step to enable both production lines to run closer to their ideal speeds, and the study results inform the business case for redesign of the furnace or capital investment for new technology.

Also found to be significant in this study are factors under the influence of management, such as production scheduling, learning curve, unambitious target setting, crew differences and machine breakdowns from improper maintenance. This finding indicates that sizeable improvements in speed loss can be made by applying lean and TPM approaches, such as the speed loss method applied by Nakajima (1988) and the 5 Whys analysis used by Benjamin, Marathamuthu and Murugaiah (2015). Actions to further optimise production planning and to implement best practice across crews should also be taken.

While the coefficient for the learning curve variable implies that operators reduce their speed loss with time, the linear relationship is limited to interpolation within the
analysed data set and should not be extrapolated. Extrapolation would assume that the speed loss can be minimised indefinitely as operators gain more experience, which is not feasible.

Production stops and material issues are not significantly related to the percentage speed loss for either production line studied. This finding suggests that while these operational interruptions may catch operators’ attention in the data as they affect speed loss, they are relatively minor compared to the natural fluctuations inherent in the process technology and human resources. Here, the benefit of applying more advanced statistical techniques to the analysis of speed loss in process manufacturing settings can be seen.

Of the factors affecting speed loss identified in the literature, this parallel case study identifies and corroborates the significance of machine reliability, technological and environmental limitations, natural process variation from raw material dosing, operator training, production scheduling, quality constraints and natural process variation from raw material dosing. No evidence is found in the analysis to support the impact of equipment age, raw material mix or capacity utilisation on speed loss. The impact of product variety on speed loss is seen indirectly through runtime and order sequencing, as discussed in the literature (Berry and Cooper 1999).

This study is potentially limited by its determination of speed targets, which might have been skewed by outliers. The researchers took actions to clean out obvious outliers to avoid this problem. Additionally, it is possible that critical variables are omitted from the regression model unbeknownst to the researchers. Another study limitation is possible measurement errors in the sensors, which may have contributed to variability in the dependent and independent variables.

This study contributes a list of factors leading to speed loss and a parallel case study quantifying the impacts of the identified factors on speed loss on two insulation production lines. The results validate speed loss factors described in the literature from a process manufacturing perspective and highlight the importance of technology and management-related factors in reducing speed loss. Similar results are expected to be found in other capital-intensive, continuous-flow manufacturers (e.g. producers of foam mattresses, frozen baked goods and steel beams) due to the high rigidity and integration of the equipment. The GLS regression approach utilised in this study is useful for practitioners to (1) identify factors related to speed loss; (2) set appropriate OEE and speed loss targets for unique production contexts; and (3) prepare business cases for capital investment to overcome technology-related speed loss factors. Future research should explore the impact of capacity utilisation, equipment age and maintenance techniques on speed loss, variables not directly addressed in this study.

Acknowledgements
The researchers thank the Innovation Fund of Denmark for its sponsorship of this research.

References


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<th>RUNTIME</th>
<th>NEXTSP</th>
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Appendix I, Pearson’s correlation coefficients for independent variables on L1
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Appendix 2. Pearson's correlation coefficients for independent variables on L2.
| **STUDY F** |
|-----------------|--------------------------------------------------|
| **Paper title** | Product portfolio optimization based on substitution |
| **Authors**     | Anna Myrodia, Alexandria (Moseley) Trattner and Lars Hvam |
| **Paper type**  | Conference paper                                  |
| **Outlet**      | *International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 2017* |
| **Paper status**| Part of the conference proceedings                |
Product Portfolio Optimization Based on Substitution

A. Myrodia¹, A. Moseley¹, L. Hvam¹
¹Department of Management Engineering, Technical University of Denmark, Kgs. Lyngby, Denmark (annamyr@dtu.dk)

Abstract - The development of production capabilities has led to proliferation of the product variety offered to the customer. Yet this fact does not directly imply increase of manufacturers’ profitability, nor customers’ satisfaction. Consequently, recent research focuses on portfolio optimization through substitution and standardization techniques. However when re-defining the strategic market decisions are characterized by uncertainty due to several parameters. In this study, by using a GAMS optimization model we present a method for supporting strategic decisions on substitution, by quantifying the impact of those parameters. Empirical evidence supplements the research, where a case study from an industry company producing construction material demonstrates the results.

Keywords - Product substitution, complexity management, product variety, portfolio optimization

I. INTRODUCTION

The production of several product variants in high quantities is intrinsically connected with increasing profitability. The more products a manufacturer offers, the greater market share can be covered, which leads to more customers and earnings. However, research and experiences from practitioners have shown that this is not always applicable in real life cases. The increasing variety offered to the customers often has a reverse impact, by causing confusion. The increasing number of products and services offered by companies is also related to the increasing complexity, both product - and process - wise. Product substitution is considered as part of the solution to handle this increasing complexity. The term “economies of substitution” describes the manufacturing strategy that companies apply, regarding reusability of components within a company’s product range [1].

From the retailers’ point of view, the focus has been placed on the customer-end, where the retailer has to be able to order the right products and the proper quantities that are required from the customers [2]. In other cases, the customer has to decide on which product can be a proper substitute, for example when the first-choice product is out of stock [3]. Customer-driven substitution takes place when the demand cannot be satisfied [4]. The sales person, or even the customer himself, decides on the substitution of one final product with another [5].

Product substitution is categorized into two classes: vertical and horizontal [6]. Vertical substitution can be one-way, where the product of higher index (i.e. quality, price, value) can substitute a product of lower index, or two-way, where products of both higher and lower indexes can substitute each other [7]. One-way vertical substitution is also mentioned as downward substitution [8]. Horizontal substitution, where products of similar quality or value substitute each other, is distinguished as being either centralized or decentralized. Current research refers to this classification as firm-driven (centralized) and customer-driven (decentralized) [9].

This study focuses on one-way firm-drive substitution at a finished goods level, as the customer-driven substitution cannot be controlled [10]. By using an optimization model, the manufacturer makes the decision on substitution, and decides on the variety.

II. LITERATURE REVIEW

Linear programming models have been widely used to support this strategic decision-making process. Reference [5] develops a model to determine the optimal component quantities including component substitution, so as to maximize manufacture’s profitability. Firm-driven component substitution is considered due to lack of inventory; production cost, distribution cost and revenue loss are the parameters taken into account. Reference [11] develops a model to estimate the specific products to be produced, their quantities and how these products can satisfy the demand. Costs taken into consideration in the model cover setups, production, stock out and substitution. This refers to one-way downward substitution, where the demand of a certain product can be satisfied by a specific range of products. The impact of product substitutability on optimal capacity and flexibility is discussed by [12], where they also consider pricing as a parameter when planning the product assortment. Inventory management and cost reduction are also advantages of an effective product substitution model [8].

Several researchers have considered product substitution based on the demand. Reference [13] creates a model in order to tackle the lot sizing problem by substituting the products of low quality with high quality products. On the other hand, [14] develops algorithms in order to define the optimum lot size between two products; the product in lower demand can substitute the product in higher demand, with or without the need for redesign.

Another crucial aspect of firm-driven product substitution is the decision on the parameters that should be taken into account. Demand, average lead time, inventory level, purchase cost, holding costs and penalty costs as the main parameters that influence the decision making process discussed by [3, 9, 15, 16]. Price is another
important parameter when deciding products to be eliminated and substituted by others [16]. This can also lead to a loss in profit when substituting a product of higher index with one of lower index, and keeping the price of the lower one [15]. Demand variation, expected profit, cost, inventory level, competition and demand correlation are parameters included in the algorithm developed by [9] to examine both centralized and decentralized partial product substitution problems. Technical characteristics, attributes and functionalities are essential parameters to be considered when substituting products to ensure the needs of customers are met. This affects both one-way and two-way substitution.

The goal for centralized product substitution is on one hand to reduce the number of final variants offered to the customer, while maintaining the solution space [17]. On the other hand, the goal is to increase profitability and performance of the optimized product portfolio by keeping the true profitable products and eliminating the less value adding ones [18]. This approach complies with the one-way centralized substitution, where the substitution index is the profitability of the products and the manufacturer is defining the products to be substituted by more profitable ones.

The ABC product categorization, based on the Pareto principle, can be used for identifying the products to be considered in a substitution model [19]. One approach for one-way substitution is to replace the less profitable C products with more profitable A products. This decision can be made based upon the similarities among across the A and C products in regards to their technical characteristics. However, recent studies have shown that an even more profitable substitution strategy is the one that takes into account substitution within the A products, the “silent-killers” [20]. By keeping the high-runners and replacing the lower A products, leads to even higher increase in the revenue and reduction of costs [20].

This research contributes to the existing knowledge of systematic product substitution based on linear optimization. To the best of our knowledge, there is no model that includes together substitution parameter, degree of substitutability, contribution margin (CM) and related sales. Therefore we develop a model that simultaneously optimizes aspects identified in the literature as relevant for one-way centralized product substitution: degree of substitution, product profitability and linked revenue.

III. METHODOLOGY

A mixed integer program (MIP) was developed to optimize the product assortment based on relevant product portfolio optimization concepts from [3, 9, 15,16], including margin, substitution, related sales, and minimum feature requirement techniques. The model is a decision support tool which uses historical data to recommend products to keep and remove in the coming year to maximize profitability. The model was developed and solved in General Algebraic Modelling System (GAMS) optimization software [21] using actual sales and product data from a case company. The GAMS model takes the following form:

A. Parameters

\[ P = \text{the set of all products} \]
\[ F = \text{the set of all features} \]
\[ NS_p = \text{Net sales per product } p \text{ in Euros, where } p \in P \]
\[ CM_p = \text{Contribution Margin per } p \text{ in Euros, where } p \in P \]
\[ CC = \text{Fixed complexity cost per product for master data management, stock management, sales, etc. in Euros} \]
\[ L = \text{the percentage of related sales lost} \]
\[ RS_{p,q} = \text{Related sales, the percentage of units } q \text{ that were sold in the same orders as } p, \text{ where } p \in P \text{ and } q \in P \]
\[ Sub_{p,q} = \text{Percentage of sales substitutable from product } q \text{ to product } p, \text{ where } p \in P \text{ and } q \in P \]
\[ F_{p,f} = \text{Feature matrix which equals 1 if product } p \text{ has feature } f, \text{ and equals 0 if otherwise, where } p \in P \text{ and } f \in F \]
\[ FReq_f = \text{The minimum number of products needed to fulfill market requirements for feature } f, \text{ where } f \in F \]

B. Variables

\[ Q_p = \text{Factor increase in sales for product } p, \text{ where } p \in P \]
\[ K_p = \text{Binary variable to indicate if a product is kept in the assortment (1=kept, 0=removed), where } p \in P \]

C. Objective Function

\[ \text{Maximize } \sum_{p \in P} CM_p * Q_p - CC * K_p \]  

(1)

D. Constraints

\[ Q_p \leq 1000 * K_p, \quad \forall p \in P \]  

(2)
\[ K_p \leq 2 * Q_p, \quad \forall p \in P \]  

(3)
\[ NS_p * Q_p \leq NS_p + \sum_{q=1}^{NS_p} Sub_{p,q} * (1 - K_q) \]  

(4)
\[ -L * NS_p \sum_{q=1}^{NS_p} Sub_{p,q} * (1 - K_q), \quad \forall p \in P \]  

(5)
\[ \sum_{p \in P} F_{p,f} * K_p \geq FReq_f, \quad \forall f \in F \]  

(6)

The objective function in equation (1) maximizes the new CM (CM from last year scaled by the factor increase in sales) minus the complexity cost from keeping a number of products in the portfolio. It is assumed that fixed complexity cost per product [19], CC, is equal for all products that are kept in the assortment.

Equation (2) ensures that if a product is not kept, then the factor increase in sales is zero and that if any product is sold (\(Q_p > 0\)), then the product is kept. Equation (3) ensures that if a product has zero sales, then the product is not kept in the assortment and that if the product is sold, a minimum of 50% of the volume from last year is sold in the new scenario. Equation (4) calculates the new revenue for a product including the sales gained from substitution...
and excluding lost sales from product removal with related sales. This was formulated based on the assumption that if a product with related sales is removed from the assortment, the sales for other products which had related sales with the product in question are lost at the rate of factor $L$. Factor $L$ is determined as a constant in this model, but could be parameterized per product in other applications. Equation (5) ensures the feature requirements are met. Equation (6) constrains the variables to the set of positive real numbers and binary values accordingly.

The parameter $Sub_{p,q}$ was determined using two steps: determining the match in technical characteristics between two products and determining the percentage of revenue transferable between two substitutable products. To determine the match in technical characteristics between each pair of products, referred to as $Match_{p,q}$, four key product features were converted to numerical values using a normalized scale from 1 to 10 for all products. The feature values are stored as $f_{1,p}$ for feature 1 and product $p$, etc. $Match_{p,q}$ is then calculated using equation (7). The value $x$ in equation (17) is a parameter which augments the match between products. For this study, $x = 2$. No weights are assigned to features in this initial study since all attributes are of equal importance when determining substitutability.

$$Match_{p,q} = \left(\frac{\min(f_{1,p} - f_{1,q})}{\max(f_{1,p} - f_{1,q})}\right)^x \left(\frac{\min(f_{2,p} - f_{2,q})}{\max(f_{2,p} - f_{2,q})}\right)^x \left(\frac{\min(f_{3,p} - f_{3,q})}{\max(f_{3,p} - f_{3,q})}\right)^x \left(\frac{\min(f_{4,p} - f_{4,q})}{\max(f_{4,p} - f_{4,q})}\right)^x$$

In the second step, the value for $Sub_{p,q}$ is calculated by dividing the maximum percentage of revenue substitution possible per product by the number of products meeting the minimum $Match_{p,q}$. For example, if the minimum $Match_{p,q}$ is set to 100%, product $p$ has 100% match with 4 other products in the assortment, and the maximum revenue substituted is 50%, then each of the 4 other products has a 12.5% revenue substitution percentage with product $p$.

Though the model is relatively small for a MIP, it is anticipated to perform better than manual substitution methods since the model can simultaneously consider over 5,000 constraints for a portfolio of 1,000 products during optimization.

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IV. RESULTS

A. Case study

The company selected as a case study for this research is a manufacturer of building components that operates worldwide with production sites in Europe, Asia and North America. It has 10,500 employees and a yearly turnover of approximately 2 billion Euros for 2016. The company is facing an increasing number of final variants, where some of them have become obsolete, but still maintained in the ERP system.

Data collection was performed in 2014 using the ERP system of the company and it includes the products from the Germany market. The initial number of final variants is 1600; due to limitations on data availability, only 737 final variants are included in this case research. For the current analysis, the 38 recently introduced products are not taken into consideration for the substitution decision, since they are not considered mature yet.

The final 699 products included in the analysis belong to 23 product families and have 139 product features. For these products, financial data and technical characteristics are obtained from the database of the company. Financial data include the price, revenue, cost and contribution margin. Technical characteristics are length, width, thickness and density.

B. Analysis

The first step of the analysis includes the ABC categorization of the product assortment. The products are grouped as A, B or C based on the net revenue. The result of this categorization shows that 120 products are characterized as A, which are responsible for 80% of the total net revenue, 156 products as B corresponding for 15% of the net revenue and 423 as C, the long tail of products generating 5% of the net revenue. These results indicate the products that are candidates for substitution.

The next step is to perform the manual portfolio optimization using the ABC analysis results to identify the possible candidates for substitution. The constraints and parameters used in the manual substitution are the same as in GAMS model. The most significant parameters for this case are defined after consultation with product managers and experts from the company. However, the results vary between the two substitution methods. As expected the results generated from the GAMS model outnumber the manually substitution.

To examine the impact of substitution on profitability optimization, three scenarios are developed. The scenarios vary in the degree of substitutability, the increased maintenance cost, the related sales, the number of sales that can be transferred from the substituted product, and the matching percentage of the technical characteristics (see overview in Table I). The new CM and NS from last year multiplied by the factor increase (or decrease) in volume per product, $Q_p$, from the optimization model.

The first scenario is the conservative one, which requires 100% match in the technical characteristics of the products to be candidates for substitution. Table II illustrates the results, including the comparison between the current state, the manual and the systematic substitution.
From Table I it can be seen that an increase in $CM_{adj}$ by 13% from the manual substitution and 15% from the systematic substitution is expected. For both substitution methods the revenue is expected to be decreased due to a decrease in the number of sales. Similarly, the fixed complexity costs and the number of product variants are expected to be reduced.

The second scenario is the pragmatic one as it assumes a 98% match of the technical characteristics of the products. The results are shown in Table III.

This scenario provides an even higher expected increase in the $CM_{adj}$: 18% from the manual substitution and 22% from the systematic one. The loss in sales, hence the revenue, is not changed from the conservative scenario, however the final number of products are further reduced in the pragmatic scenario. This explains the reduction in fixed complexity costs that is calculated.

The third scenario is the optimistic one, where the minimum match of technical characteristics among the products is 95%. The results are presented in Table IV.

Overall, the results from both substitution methods are relatively aligned. Another interesting finding is that the more flexible the constraints regarding substitution become along the scenarios, the more the difference in $CM_{adj}$ becomes between the two substitution methods. That can be explained by the fact that in the manual substitution, given a huge data set, the overview is easily lost and very likely for the person or the team performing the calculation will make mistakes.

C. Discussion

The results from the scenarios indicate significant potential for implementing the product substitution strategy. Both the manual and the systematic substitution with the GAMS model show that the released benefits in terms of increased $CM_{adj}$ can be of great importance in a company. Even in this case study, where only 699 products were included in the analysis (corresponding to 44% of the total number of variants offered in this market), product substitution can be proven rather profitable.

The comparison between the results and the financial calculations from the manual and the systematic substitution method (GAMS) vary among the different scenarios, as discussed before. The systematic approach however, provides a better overview. Since the calculations and the actual recommendations are generated by the GAMS model, the human factor error is eliminated. The systematic substitution method is also faster (i.e. solve time is 1.78 seconds for the conservative scenario in GAMS but 38 hours for the manual) and can handle much more information in a more efficient way, than the manual substitution method.

VI. CONCLUSION

The purpose of this research is to evaluate product portfolio optimization based on product substitution methods. First, we assess the existing literature regarding methods for product substitution and identify parameters and constraints used in one-way centralized product substitution. Additionally, the literature is examined in particular for systematic ways in product substitution. The findings indicate linear optimization methods can contribute significantly to automating the decision making process for portfolio optimization.

Based on these, a case study is conducted in a manufacturing company making building components. First, the financial performance of the products is evaluated and based on the results possible candidates for substitution are identified. Then, the relevant parameters for substitution are defined and three scenarios are developed, by slightly changing the constraints. Finally, the scenarios are performed both with manual substitution and systematic, by utilizing a GAMS optimization model. The results of the case study show significant potential savings.
by using either of the substitution methods. As expected, the systematic substitution provides better results for the company than the manual substitution method, in terms of higher profitability and reduced complexity costs. In this particular case there is an improvement of the CM by 2% on average for the different scenarios. Therefore, there is a noteworthy potential for the application of the optimization tool in product substitution, as even minor improvements of the CM correspond to significant earnings for the companies.

After defining the constraints and the parameters of the model, which are dependent on the user, the model optimizes the profitability and based on that makes recommendations regarding the product substitution. This approach can provide valuable input in comparing different market segments in terms of the profitability of the offered variety. Additionally, by changing the matching parameters based on the attributes of different products can be applied to different companies.

However, there are certain limitations regarding this research. This is a single case study research and more companies need to be examined to enable generalizability of the results. In addition, the GAMS model is a prototype and is developed by the research team, who are not experts in the field. In this model the substitution takes place within one market, while it could be expanded and include multiple markets and enable comparison across them. Moreover, more constraints can be added and with particular focus on the accuracy of the linked revenue and estimated demand. Based on these limitations further research is needed within the linear optimization research field. Therefore, there is room for improvement to achieve better and more accurate results.

In conclusion, this paper contributes to the literature, in particular to the complexity management theory, by applying the linear optimization concept for product substitution. It also contributes to practice by suggesting a developed tool for substitution and providing an example of its application in a real industrial setting. Decision making on product substitution for portfolio optimization is a recognized challenge in the companies studied because it is hard for a human to make all the calculations and take into consideration all the constrains required.

REFERENCES

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Framework for analysing speed losses in process manufacturing firms
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Abstract
This paper proposes a framework for the analysis of speed loss in a process manufacturing context, which is developed based on the existing literature. The framework is structured into seven steps: (1) Secure the human resource(s) who will lead the speed loss programme. (2) Ensure data readiness to begin the speed analysis programme. (3) Determine the standard production speed for each product using the designed capacity or the demonstrated maximum sustainable performance from the historical data. (4) Calculate the speed loss for the process using the ideal production speeds. (5) Formulate hypotheses on possible causes of speed loss, and gather relevant data. (6) Quantify the impact of the causes of speed loss. (7) Identify significant causes of speed loss, and eliminate them. The framework is tested in a case company in the process industry, which demonstrates the framework’s relevance and usefulness.

Keywords: speed loss, process industry, overall equipment effectiveness, TPM, productivity improvement

Acknowledgements
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1. Introduction
In an era of increasing price competition, manufacturers utilise various methods to maximise efficiency and lower product costs. Total Productive Maintenance (TPM) and its flagship measure, overall equipment effectiveness (OEE), are examples of such methods that are increasingly adopted by manufacturers aiming to improve process stability and gain competitive advantage [1–4]. As a manufacturing approach introduced in 1971, TPM focuses on the concept of preventive maintenance and encourages all production employees to be proactive in maintaining equipment. Designed to quantify six major types of losses in production environments, OEE is a simple metric that helps manufacturers identify areas for improvement regarding their equipment’s performance.

One of the six loss categories of OEE, which has received little attention, is speed loss, that is, the misalignment between the designed and the actual operating speeds of a piece of equipment [5]. Case studies in the operations management literature have shown that reduced speeds can cause a 9–15% loss of manufacturers’ production capacities [6,7]. The effect is even larger in highly automated production and packaging processes, often found in the process industry [5,7]. Speed loss is typically caused by equipment defects, inadequate maintenance, equipment and tool wear, excess capacity, operator inefficiency, machine breakdowns, stoppages and setup times [8–11]. These factors have even greater impacts on large-scale, continuous and integrated processes, such as those found in the process industry, where the lack of buffer inventories allows interruptions to affect downstream processes [7,11]. Addressing the speed loss of a process manufacturer, such as a producer of chemicals, steel or paper, is further complicated by many interacting process parameters, which can simultaneously reduce production speed, making it difficult to distinguish one parameter’s effect from that of another.

In manufacturing companies, speed loss is often unmeasured due to the difficulties in collecting the needed data, determining operating speeds designed for complex systems and addressing the causes of speed loss (also referred to as speed loss factors in this paper) [6,7,12]. The neglect of speed loss is likely heightened in process manufacturing companies, which have been slower to adopt improvement methods, such as Lean and TPM, due to constraints in their manufacturing processes. For example, the long setup times required for large-scale, dedicated equipment in process industries make it difficult to implement small lot sizes and improve facility layouts [13].

Despite the significant impact of speed loss on operational performance, the TPM literature has a dearth of solutions that specifically address the issue [8]. Furthermore, the
literature does not provide any method to reduce the speed loss incurred by process manufacturers. Benjamin, Marathamuthu, and Murugaiah [8] present a framework to identify potential causes of OEE speed loss in a Lean manufacturing context. However, their approach considers each factor individually rather than adopting a more holistic view of all the factors and how they influence one another. Researchers have called for industry-specific OEE measures and methods that tailor to the unique needs of manufacturing processes [14], and the process industry presents a substantial opportunity for such customisation.

This paper develops a framework for the assessment of speed loss in a process manufacturing context, which is tested in a case company that produces insulation materials. The identified variables are specific to the studied industry context, but the presented framework is applicable to various process manufacturing contexts. Using the methodology presented in this study, companies can utilise a powerful tool to effectively address and reduce speed loss in their processes. Additionally, industry practitioners will benefit from a structured methodology that has been tested using a case study, which they can then use to improve their industrial assets’ effectiveness.

The remainder of this paper is structured as follows. First, Section 2 reviews the relevant literature. On this basis, Section 3 develops a framework for the assessment of speed loss in manufacturing processes. The research method is described in Section 4. Section 5 presents the case study to which the framework is applied. The results of the case study are discussed in Section 6. Section 7 ends the paper by drawing the conclusions.

2. Literature review
This section provides an overview of speed measures and OEE, along with a summary of available speed loss frameworks.

2.1 Speed measures
As a concept, the speed of a production process assumes a wide array of names in the literature, including cycle time [5,11], throughput [15], process productivity [16] and others. As this paper addresses production speed in a process manufacturing context where operations are highly automated, labour productivity is not a significant factor in determining overall production speed [13].

Throughput, meaning the average output of a production process per unit time, is a widely used measure of operational performance [15] and is commonly used to communicate the capacities of process industry production systems [17]. The terms throughput and speed are used interchangeably throughout this paper.

2.2 OEE and speed loss
The primary method of calculating OEE was first published by Nakajima [5]. He describes OEE as a measurement encompassing six major losses in production systems, as follows:

 Availability losses (A)
  1. lost time due to equipment breakdowns that can reduce productivity and increase the amount of scrapped products;
  2. lost time due to equipment setup and adjustment;

 Performance losses (P)
  3. lost equipment productivity due to interruptions or temporary malfunctions;
  4. lost production speed, measured as the difference between the designed and the operating speeds of a piece of equipment;

 Quality losses (Q)
  5. lost productivity due to defects and rework; and
  6. scrapped products created during equipment start-up.
Thus, OEE can be calculated by first computing its three submeasures: availability ($A$), performance ($P$) and quality ($Q$). These three submeasures are then multiplied to obtain OEE. As speed loss is of primary interest in this study, Equation 1 depicts the calculation of $P$, including the effects of reduced speed and small stops [11]. Equations 2 and 3 show how speed efficiency (and speed loss) can be derived from Equation 1. Since process industries typically do not measure output in cycle time (as done in discrete industries), Equations 2 and 3 are expressed in terms of throughput.

$$P = \frac{\text{Ideal cycle time}}{\text{Actual cycle time}} \times \frac{\text{Actual cycle time} \times \text{Output}}{\text{Operating time}}$$  \hspace{1cm} (1)

$$\text{Speed efficiency} = \frac{\text{Ideal cycle time}}{\text{Actual cycle time}} = \frac{1 / \text{Ideal throughput}}{1 / \text{Actual throughput}} = \frac{\text{Actual throughput}}{\text{Ideal throughput}}$$  \hspace{1cm} (2)

$$\text{Speed loss} = 1 - \frac{\text{Actual throughput}}{\text{Ideal throughput}}$$  \hspace{1cm} (3)

- **Ideal cycle time**: theoretical time for the equipment to process a single unit
- **Actual cycle time**: actual time for processing a single unit
- **Output**: total units produced by the equipment
- **Operating time**: equipment operating time, excluding planned stops for holidays, regular maintenance and low demand
- **Ideal throughput**: theoretical units produced per unit time (inverse of cycle time)
- **Actual throughput**: actual units produced per unit time (inverse of cycle time)

Other variations of OEE are discussed in the literature, such as De Groote’s [18] study, which calculates the actual amount of production and compares it with the planned amount of production for a fixed time period, and the SEMI [19] publication, which expresses OEE in terms of time. Further variations of the OEE calculation allow for weighting the individual subcategories based on a firm’s strategic priorities [20] and the integration of OEE with equipment reliability analysis to compute Overall Factory Effectiveness [21].

Measuring the ideal cycle time for a system consisting of serial machines must consider the theoretical processing rates of each piece of equipment for different product types, the number of product types and the total time [22].

### 2.3 Existing frameworks

The literature identifies three frameworks that are specifically designed to reduce speed loss. First, Nakajima [11] proposes a four-step method of approaching speed loss in factories, as follows:

1. Achieve the standard speed of each product.
2. Increase the standard speed of each product.
3. Achieve the designed speed.
4. Surpass the designed speed.
As speed is increased, other issues may arise in the form of mechanical breakdowns or reduced product quality, thus signalling opportunities for improvement. This approach is designed to expose hidden problems, such as improper testing in the equipment design phase, inadequate maintenance, inappropriate setup and tuning, among others [11].

The second framework is also proposed by Nakajima [11]. He elaborates on a systematic approach to speed improvement, including the following 14 steps:

1. Determine present levels of speed, bottleneck resources, downtime, stop frequency and conditions producing defects.
2. Check the difference between the specifications and the present situation.
3. Investigate past problems.
4. Investigate processing theories and principles.
5. Investigate mechanisms.
6. Investigate the present situation.
7. List problems.
8. List predictable problems.
9. Take remedial action against predictable problems.
10. Correct problems.
11. Perform test runs.
12. Confirm the mechanism.
14. Perform further test runs.

While Nakajima’s [5] four-step method is appropriate for minimising speed loss, his approach does not help an organisation understand speed loss and its causes. The four-step approach also lacks guidance for structuring speed data for analysis and determining standard speeds in different production contexts. The second framework with 14 steps offers more guidance for identifying and addressing the mechanisms that cause speed loss. However, it scarcely aids practitioners in the necessary statistical methods to decipher the importance of variables in complex process manufacturing contexts.

The third framework identified in the literature utilises the 5-why technique, combined with the Pareto analysis and a kaizen event, concepts popularised in Lean manufacturing [8,23–25]. The 5-why technique has been proven effective in reducing the speed loss incurred by a Malaysian metal barrel manufacturer, equivalent to USD 32,000 [8]. The Pareto analysis is used to examine the causes of other OEE losses and prioritise improvement activities in discrete processing industries [10] but is not ideal for analysing a continuous processing line due to the many interacting variables affecting throughput. A more empirical approach is needed to discern the potential effects of the many variables at play when assessing speed loss in the process industry.

Due to the limited approaches to addressing speed loss [5,8,26], it can be concluded that the TPM and the operations management literature lacks systematic methods of uncovering the factors related to speed loss, measuring their relative relationships in process manufacturing environments and proposing recommendations for minimising speed loss.

3. A framework for analysing speed loss in process manufacturing
This section develops a framework for understanding and addressing the speed loss incurred by process industry manufacturers. This aim is achieved by combining methods from the TPM literature with regression analysis. The framework’s goal is to provide some means to quantify speed losses in manufacturing processes through attributable causes (e.g., product
variety, production scheduling, inadequate maintenance), thereby enabling appropriate corrective or preventive action.

To structure a comprehensive analysis of speed loss in process manufacturing firms, the seven-step framework shown in Table 1 is proposed. As seen in the table and further explained in the following paragraphs, these seven phases are based on the topics addressed in the existing literature. Speed loss is assumed to be a known cause of major loss in the production system to which this framework is applied. The framework follows the necessary steps for calculating performance efficiency [5] but incorporates a multiple regression analysis component, which has been shown as applicable to process manufacturing settings [16,27,28].

Table 1. Proposed speed loss framework

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<th>#</th>
<th>Step</th>
<th>Description</th>
<th>References</th>
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<tr>
<td>1</td>
<td>Secure the human resource(s) who will lead the speed loss analysis programme.</td>
<td>Identify an individual responsible for data collection, analysis and regular reporting to relevant stakeholders.</td>
<td>[29–32]</td>
</tr>
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<td>2</td>
<td>Ensure data readiness to begin the speed loss analysis programme.</td>
<td>Assess whether the required data for calculating speed loss is available in the firm. If unavailable, then provide a manual or automatic methods to collect the data.</td>
<td>[6,7,12,16,33–35]</td>
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<td>3</td>
<td>Determine the target speed for each product.</td>
<td>Identify the designed speed of the equipment from the manufacturer. If the designed speed is unavailable, use the maximum demonstrated, feasible and sustainable speed from the historical data.</td>
<td>[7,9,12,17,26,36,37]</td>
</tr>
<tr>
<td>4</td>
<td>Calculate the speed loss for the process.</td>
<td>Apply the speed loss calculation in Equation 3. Speed loss can be calculated at the batch, product, day or minute level, with the calculation complexity varying with the level of product-mix heterogeneity.</td>
<td>[5,22]</td>
</tr>
<tr>
<td>5</td>
<td>Formulate hypotheses on possible causes of speed loss, and gather relevant data.</td>
<td>Develop a set of expert hypotheses by interviewing process engineers, production supervisors, design engineers and operators to uncover which factors may be related to speed loss, ensuring a logical causal link for each hypothesis. Gather the relevant data.</td>
<td>[38]</td>
</tr>
<tr>
<td>6</td>
<td>Quantify the impact of the causes of speed loss.</td>
<td>Apply the appropriate regression analysis technique to the aggregated dataset to identify statistically significant factors.</td>
<td>[16,39–42]</td>
</tr>
<tr>
<td>7</td>
<td>Identify significant causes of speed loss, and eliminate them.</td>
<td>For each factor, use the statistical significance and the coefficient magnitude and direction to create a prioritised list of actions to mitigate speed loss.</td>
<td>[8,11]</td>
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The order of the seven steps reflects a combination of change management principles, root cause analysis, statistical regression and systematic improvement. In Step 1, the framework suggests identifying the human resources who can lead the analysis and improvement efforts, deemed critical to initiating change management and Lean projects [29,31]. Assessing data readiness is placed as Step 2 since studies have found that companies often do not record cycle time or throughput data in relation to speed targets [6,12]. Similarly, Step 3 (determining the target speed per product) is included because many firms have been found using unambitious speed targets, which are consistently exceeded [7,12]. Thus, it is
important to address the appropriate speed target setting in the framework. The order of Steps 2, 3 and 4 follows a logical, linear structure, where speed targets cannot be determined without production speed data, and speed losses cannot be calculated without speed targets. Formulating hypotheses on the causes of speed loss is placed as Step 5, after data collection and speed loss quantification, so that operators, engineers and managers can associate the production phenomena with the quantified loss of production speed before hypothesising on possible causes of speed loss [11]. Formulating hypotheses on possible causes of speed loss before obtaining transparent speed data and calculations would evoke educated guesses rather than informed hypothesis development. Step 6 logically follows Step 5 as the means of statistically testing the hypotheses on the causes of speed loss by using regression. Without a statistical testing step, operations managers risk addressing the greatest perceived causes of speed loss, which may not reflect the actual main causes of speed loss in production. Step 7 then prescribes that the quantified causes of speed loss be ranked in order of significance and potential and be used to drive improvement activities, following Nakajima’s [5,11] well-documented approaches.

This framework differs from the others found in the literature as it addresses key issues tailored to the process manufacturing industry. Additional emphasis is placed on determining the ideal throughput in process manufacturing firms, which is not always a straightforward task. The framework adds an empirical analysis step by regressing potential factors against the observed speed loss to quantify the correlation between the variables. This step is absent from previous speed loss studies, which have primarily examined discrete production facilities [8,26,43].

In practice, the framework would be used to drive root cause analysis initiatives and gain a better understanding of the factors affecting speed loss. The analysis in Step 6 is performed as a desk study and can be executed at intervals to track changes in the most relevant factors. This framework does not replace standard production performance indicators but is a tool to supplement continuous improvement initiatives in relation to lost production speed.

In the following sections, each step of the framework is described in more detail.

3.1 Step 1. Secure human resource(s) who will lead the speed loss programme.
Securing the human resource(s) who will carry out the analysis and improvement efforts of a speed loss programme is a critical step to ensure the programme’s success. Kotter [31] lists creating a strong coalition to lead the change as the second of eight steps in his framework for successfully creating change in organisations. In the manufacturing context, change management projects can take the form of productivity improvements aligned with Lean, Total Quality Management, Six Sigma and TPM methods. Clear support from the top management, willingness to change and skilled workers have also been shown as success factors for Lean and Six Sigma projects in different manufacturing industries [29,30,32]. All stakeholders must possess not only the needed skill sets but also the ability to lead people in adopting speed loss analysis as an improvement mechanism and managing the daily operational tasks of adhering to a speed loss programme.

3.2 Step 2. Ensure data readiness to begin a speed loss programme.
Once the project team has been formed, it is important to assess the data readiness for a speed loss programme. Previous TPM and OEE studies have shown that many firms do not collect actual cycle time data from their equipment [6,7,12]. An accurate measurement of actual cycle time or throughput data is essential for speed loss calculation. If the necessary data is unavailable or inaccurate, the project team should initiate activities to collect cycle time data.
Manufacturers in the process industry, also referred to as heavy industry, are known to collect large amounts of data that can be analysed and used to optimise production throughput and efficiency [35]. Databases, such as the manufacturing execution system (MES) or sensor data repositories, contain a wealth of data that can include the actual cycle time data for an OEE and speed loss programme [12]. Previous studies have used similar forms of aggregated production data to assess the factors impacting the labour and process productivity of automotive and process industry manufacturers [16,33,34].

3.3 Step 3. Determine the standard production speed for each product.

The theoretical or ideal speed of a process is a fundamental element in calculating the speed loss of a production line but is often unknown or not clearly defined [5,26]. The operations management literature has done little to prescribe the best practices to determine the ideal cycle time for specific production processes. However, there are related discussions about capacity planning.

The following are three measures of capacity for a manufacturing line [17]:

- **designed capacity**, calculated based on the first principles of the process plant;
- **demonstrated capacity**, a plant’s maximum sustainable, observed throughput, which can be known by testing the plant for regulatory purposes; and
- **effective capacity**, the actual capacity, considering the days of availability and the effectiveness of the bottleneck process.

When calculating the $P$ and the OEE of a process manufacturing plant, it is unclear whether the designed capacity or the demonstrated capacity should be used as the ideal cycle time [5] in Equation 3. Furthermore, it is not a straightforward task to determine either designed capacity or demonstrated capacity for highly variable processes.

An integrated production line comprising a series of different machines designed for continuous production may not come with a readily obvious designed capacity. In continuous-flow production lines, several individual machines are linked in series, with each machine having its own ideal cycle time and one process and typically acting as a bottleneck machine, limiting the entire line’s production rate [17]. When the product mix is high, the bottleneck machine can shift in the process, complicating the determination of the designed capacity [36]. To overcome the challenge of determining a process plant’s designed capacity, Litzen and Bravo [37] suggest examining historical data to identify each equipment’s maximum throughput, noting that this does not necessarily determine the true equipment capacity. For more complex processes, simulation software may be needed to model throughput variations and obtain a reasonable capacity estimate [37].

The most comprehensive definition of a process manufacturer’s ideal capacity is presented by Ogle and Carpenter [17], who define the maximum capacity of a chemical process as the highest production rate that

- considers production restrictions in the existing equipment, labour and materials (e.g., product mix);
- enables a sustainable throughput level for an extended and specified time interval;
- assures that a product is produced to fulfil quality requirements; and
- neither violates the operating limits for safety, health or the environment nor hinders the production capability of the equipment.

This definition of maximum capacity is used to quantify the ideal cycle time for process manufacturing lines in this framework. It is recommended that an ideal cycle time be determined per product type because bottlenecks can shift on serial lines, depending on the product being produced [9].
3.4 Step 4. Calculate the speed loss for the process.
With the actual cycle time data gathered and the ideal cycle time determined per product type, Equation 3 can be applied to determine the speed loss in terms of units of lost production. This calculation can be performed for different periods (e.g., production batch, shift, day) to suit the purposes of the company performing the speed loss analysis. Calculations of performance and speed loss in OEE are widely documented in the TPM literature [11,22] and are adapted in this study to reflect the emphasis on throughput in the process industries.

3.5 Step 5. Formulate hypotheses on possible causes of speed loss, and gather relevant data.
Step 5 of the framework involves identifying possible causes of speed loss and generating hypotheses that can be tested statistically. Hypotheses are descriptions of relationships between variables [38]. Employees who are knowledgeable of the production process (e.g., production supervisors, operators, process engineers and design engineers) should be interviewed to develop a set of expert hypotheses on which factors may be related to speed loss. The hypotheses should pass a basic logical test to ensure that the identified factors can affect speed loss, either directly or indirectly, on the production line. It is advantageous to interview a variety of personnel involved with the production process to corroborate the list of hypotheses and focus the remainder of the analysis.

Once a comprehensive list of hypotheses has been created, the data to test each hypothesis should be collected from the relevant databases (as discussed in Step 2). The data should be cleaned of nonessential information, such as null values, constants and outliers with an explainable cause (e.g., a broken sensor).

3.6 Step 6. Quantify the impact of the causes of speed loss.
Statistical regression analysis is carried out next on the aggregated dataset to test whether the identified factors are significantly related to speed loss. Regression approaches have been utilised to assess the impact of different factors on process productivity, product quality and manufacturing overhead costs, demonstrating the appropriateness of the method of speed loss analysis [16,27,39,40]. Selecting the appropriate regression technique depends on the level of analysis being performed. For example, when analysing production data at a batch level, the observations may be considered independent, which suggest the use of ordinary least squares regression. When assessing speed loss at the minute or the second level, the observations may exhibit a serial correlation, where one observation is related to both its predecessors and successors. This issue can be overcome by using the Cochran-Orcutt method [41] or generalized linear regression [42].

Exploratory analysis of the univariate relationship between each factor and speed loss can reveal if any variable in the dataset has a nonlinear relationship with speed loss. With this knowledge, various models can be tested to determine which formulation achieves the best model fit with a parsimonious array of variables.

3.7 Step 7. Identify significant causes of speed loss, and eliminate them.
The final model from step 6 can be evaluated from three viewpoints: the overall model fit, the significance of the individual factors, and the factor coefficients’ magnitude and direction. Statistically significant factors (p < 0.05) can be deemed related to speed loss with a high degree of confidence. However, these variables cannot be claimed to cause increased or decreased speed loss without further argumentation or analysis. An example of such
argumentation is a physical relationship between input and output, which would underpin the significance of the input variable’s relationship with speed loss.

The final list of significant factors with additional evidence of a causal relationship can be claimed to be related to speed loss, with a high degree of confidence. By using the relative magnitudes of the factor coefficients, a prioritised list of actions to reduce speed loss can be made to drive improvement activities using existing TPM frameworks [8,11].

4. Research method
A case study was conducted to test the proposed framework for the assessment of speed loss in process manufacturing settings. Yin [44] describes a single case study as a holistic, representative case design with a single unit of analysis (the case company). Yin [44] further argues that the case study method is appropriate for research where the boundaries between the phenomenon and the context are unclear.

The case study involved a building insulation company serving a global market (hereafter referred to as BuildCo). BuildCo has over 10,000 employees and around 20 factories that utilise the same production processes. The primary production process in BuildCo involves melting raw material, spinning molten material into fibres, adding adhesive to the fibres, compressing the fibres into a continuous slab, curing the slab, cutting the slab into discrete units and packaging each finished slab in plastic foil. BuildCo was selected as the case company as a representative of process industry manufacturers utilising large-scale, inflexible processes to mass produce materials [13]. The focus on speed loss in BuildCo provided further motivation for the collaboration.

The framework was tested over a three-month period. The case was studied through document analysis, interviews and a workshop.

The document studies included analyses of the following:
- By-product drain production log – data from 2017 and 2018 describing start times and durations of the by-product drain as registered by production operators;
- Speed loss production log – fabrication order data from an MES, including start times, end times, durations, volumes, target throughputs, actual throughputs and operator text notes on why they did or did not meet the production target;
- Crew schedule – data on which crew worked on which shift;
- Sensor data – data on variables, such as the actual primary speed and the actual recycling amount;
- OEE report on the production line – quantitative descriptions of lost production capacity due to causes, such as planned maintenance, unplanned production stops, speed loss and downstream waste;
- BuildCo’s global speed loss programme – PowerPoint presentations describing the programme; and
- Prior projects – reports describing improvement projects in other BuildCo factories.

Three one-hour interviews (digitally recorded) with the following areas of focus were held with the factory manager, as follows:
- Interview 1 – information about the background of the speed loss programme, the mechanics of the speed loss tracking tool, operators’ use of the tool, the format of the speed loss production log, and the by-product drain production log;
5. Case study

As described in the preceding section, the framework was tested with a case study in BuildCo. The production line in focus is an insulation production process, as shown in Figure 1.

![Insulation production process diagram]

The framework’s application in the case company is described using each of the framework’s seven steps.

5.1 Step 1. Secure the human resource(s) who will lead the speed loss programme.

In 2016, BuildCo commenced a large-scale, data-driven, Lean and TPM transformation programme for its operations. Using OEE as a guide to identify and prioritise the levers for improvement, the team of analysts driving the project found speed loss as one of the largest losses in production efficiency across BuildCo’s production lines. Once speed loss was prioritised as a focus area for operational improvement, each factory assembled a team of engineers, data experts and analysts, together with analysts from the company headquarters, to lead each local speed loss programme. Each factory team comprised approximately four to five members.

In the test implementation of the framework, the speed analysis was led by a team of two researchers and the factory manager, with support from operation analysts in the headquarters. As the framework was not tested entirely by BuildCo’s internal resources, the researchers acknowledge that Step 1 was only partially tested.
5.2 Step 2. Ensure data readiness to begin a speed loss programme.
Upon initial assessment of the production speeds in the MES, the research team found a high incidence of unfeasible outliers in the data, attributed to the manual registration of waste in the MES. This led the research team to examine sensor data from the production lines, which was found more accurate and reliable for statistical analysis.

Multiple measures of production speed existed in the sensor data, but the gross throughput rate of insulation fibres was found the most appropriate for analysis because it is directly measured on the line and controllable by operators in the upstream section of the production process.

The gross throughput is the summation of material flows from the spinner and the added recycling material that is created from grinding dry insulation waste in other parts of the process. The allowable recycling percentage of the gross product varies from 0% to 20% of the overall product composition based on product specifications. Achieving a high gross throughput therefore depends on the optimal functioning of the spinning process, as well as the presence of granulated recycling material for reuse.

The production of new spun fibres can be adjusted to the typical range of set points in 15–60 minutes, depending on the difference in the sequential products. Recycled content can be increased or decreased within minutes. For this reason, the researchers deemed a 30-minute time data granularity a suitable unit of analysis for capturing the variability in the process without overfitting the model with excessive data points.

5.3 Step 3. Determine target speeds.
Determining the ideal speed for each BuildCo product is a complex and occasionally political task. BuildCo’s engineers had theoretical estimations of the designed capacity for each production line, but they hesitated in stating a specific ideal throughput for a line due to the many factors that could affect process stability during operation (e.g., high product mix, shifting bottlenecks, equipment reliability, process variability, etc.). The factory management had also determined the speed targets per product based on historical data from the MES and the knowledge of experienced operators.

Comparing the factory speed targets with actual gross throughput from the sensor data shows that the targets are often overachieved, resulting in a negative speed loss. Due to the deficient factory targets, the maximum observed, sustainable and feasible throughput (MOSFT) targets were identified in the sensor data for each product [17]. This involved finding gross throughput rates that did not exceed the maximum capacity of the melting oven and were sustainable for at least 30 minutes based on the previous year’s production data.

Figure 2 compares the actual gross throughput, the factory throughput targets and the MOSFT targets for twenty hours of production. The MOSFT targets are more appropriate for speed loss calculation as they are not exceeded in the data. These results show the criticality of setting appropriate speed targets for OEE calculation in the process industry.
5.4 **Step 4. Calculate the speed loss for the process.**

By using three months’ worth of production data from the MES system and the sensors, the MOSFT targets from Step 3, and Equation 3, speed loss was calculated at 30-minute intervals of production uptime. The total time-weighted average speed loss for the production line over the three-month period was 6% when calculated using the MOSFT targets and -1% when calculated using the factory targets, indicating consistent overachievement of the speed targets. This is evidence of the difficulty in determining target production speeds in a process industry setting.

5.5 **Step 5. Formulate hypotheses on possible causes of speed loss, and gather relevant data.**

The hypotheses on the causes of speed loss in BuildCo were gathered from interviews with the factory manager and three operation analysts, as well as factory operators’ text logs. The management implemented the log in the beginning of the speed loss programme, with the intention to document perceived causes of speed loss for each batch of products from the operator perspective. The research team thoroughly read and coded the logs. Among the most operator-cited causes of speed loss were technical limitations of the melting oven (which restricted the melt flow), draining of the by-product from the melting oven, quality issues downstream in the process, technical issues with the equipment, production sequencing and batch size, and production stops. The interviews with the factory manager and operation analysts provided additional potential causes of speed loss, including work crew, product packaging type, number of products, learning curve for the factory speed targets, seasonality, raw material dosing and weather.

All the gathered causes passed basic logical reasoning tests regarding their potential relation to speed loss in BuildCo. However, some identified causes had no available...
supporting data. The final dataset included observations for 15 causes of speed loss, as well as the percentage of speed loss for each 30-minute observation.

5.6 Step 6. Quantify the impact of the causes of speed loss.
The regression analysis was performed on a linear combination of the 15 causes of speed loss, and the maximum likelihood estimates were calculated. Due to confidentiality, only a summary of the results can be discussed in this section. Of the 15 variables, which were tested and expected to influence speed loss, 12 were statistically significant. The operators’ most-cited variables in the production logs were not necessarily statistically significant in relation to speed loss. Similarly, the variables that were expected to have the most impact on speed loss did not have the highest relative effect on speed loss when evaluated together with the other variables.

The results were discussed with four operation analysts, who were surprised by these findings, particularly the influence of technological factors, such as melting oven limitations and variations in raw material dosing. For their part, the specialists had expected the by-product drain to have a more negative effect on production times (i.e., account for more speed loss). However, given the documentation presented, they ultimately agreed on the findings.

5.7 Step 7. Identify significant causes of speed loss, and eliminate them.
The significant variables were listed in order of the importance of their relation to speed loss. The information was presented to the factory manager and the operation analysts in the headquarters. Surprised by the findings regarding the most significant speed loss factors, the employees included the list of important variables in their actions for upcoming improvement activities.

6. Discussion
The case study demonstrates the usefulness of the seven-step framework for analysing speed losses in process manufacturing firms. Specifically, the seven steps ensure that all relevant aspects of speed loss analyses and reduction are considered. Furthermore, the case study shows that operators’ reports should not be uncritically accepted, but deeper analyses are needed to identify the main causes of speed loss.

In relation to other speed loss frameworks in the TPM literature, the proposed framework contributes to research and practice with its structured guidance for the identification and the empirical assessment of the causes related to speed loss in process industry firms. The framework’s focus on determining speed targets and quantifying the relative speed loss from each hypothesized cause can enable process manufacturers to gain a solid understanding of the interacting variables in their production systems before applying Nakajima’s [11] more experimentation-driven improvement approaches. One similarity between the approaches of Nakajima [11] and Benjamin, Marathamuthu, and Murugaiah [8] and the proposed framework is that all of them suggest a method of identifying potential causes of speed loss, either through investigating past problems or interviewing experts. An additional similarity is the confirmation of a logical cause-effect relationship in each hypothesised cause of speed loss, as seen in Step 13 of Nakajima’s [11] 14-step framework and Step 5 of the proposed framework. While applying regression analysis to the assessment of speed loss is not found in the TPM literature, the proposed regression approach mirrors those of other studies on throughput in process manufacturing companies [16,27,39,40], adding methodological validity to the framework. These similarities add credence to the proposed framework as a method of identifying true causes of speed loss.
Finally, the case study involves a typical company in the process manufacturing industry, which allows applying some degree of analytical generalisation [44]. Specifically, given the similarities between BuildCo and other process manufacturing companies (regarding processes, organisational structures and employees), it seems reasonable to assume that the proposed framework is applicable to other cases.

7. Conclusions
Based on the literature, this paper has developed a seven-step framework for analysing speed losses in process manufacturing firms. The seven-step framework has been tested with an insulation materials company serving a global market. The study shows that the proposed framework enables the company to identify, quantify and minimise speed losses.

The seven-step framework provides empirically tested means of addressing speed loss in manufacturing processes. This is an important type of contribution because methods of reducing speed loss in the process industry are unavailable in the existing literature. In this context, the framework includes an empirical analysis step for regressing potential factors against the observed speed loss to quantify the correlation between the variables, which is lacking in previous speed loss studies.

The case study provides insights into potential causes of speed loss. Furthermore, the study underlines the need for structured methods of identifying the actual causes of speed loss since it finds that operation analysts’ perceptions differ significantly from the actual reasons behind speed loss.

The framework provides industry practitioners with an overview of the factors causing speed loss, which may function as a guide for achieving operational improvements. Based on the experiences from the case study, the framework’s seven steps may provide companies in the process industry with an efficient tool to address and reduce speed loss in their manufacturing processes.

Although the case study represents a typical scenario in process manufacturing, limitations exist in relation to drawing generalisations. Thus, future research needs to test the proposed seven-step framework in additional cases to learn more about its potentials and possible limitations.

References
[7] Ljungberg O. Measurement of overall equipment effectiveness as a basis for TPM


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<td>Product wheels for scheduling in the baking industry: A case study</td>
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Product Wheels for Scheduling in the Baking Industry: A Case Study

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Abstract: This paper illustrates current challenges and suggests solutions within the area of scheduling in the baking industry. The analysis applies the product wheel heuristic approach of King (2009) and tests the production cycles generated using actual sales and production data from a manufacturer of frozen baked goods. The product wheel method showed to be a suitable method for application at the baked goods manufacturer and generated a 23\% reduction in setup and inventory cost at the case company. Despite the benefits, the product wheel method proved difficult to apply in a high variety setting, where an operations research model may have achieved more significant results.

Keywords: Production planning, scheduling, product wheel, process industry

1 Introduction

Rising labour costs, increased price competition, and higher demand for customised products and quick delivery times are just a few of the pressures placed on the modern baked goods manufacturer (Higgins, 2013). Bread, a staple in the diet of the Western world, has multiplied its forms through the years, spanning from baguettes to buns and flatbreads and assorted sweet treats. Behind the increased variety on the store shelf are manufacturers struggling in a competition to maintain their low-cost infrastructure while accommodating a higher product mix. Producing a wider array of products can require investment in technology in manufacturing, but can also require adjustment of operational procedures for tasks like production scheduling. It is a common goal for production scheduling to maximise service level towards the customer while minimising costs for the company (Christou et al., 2007). In doing this, the production schedule acts as a critical link between the needs of the market and the physical output of a manufacturing system in the baking industry, helping a company achieve greater flexibility (Nakhla, 1995).

Production scheduling is a decision-making process whereby the lot sizes, start and end times, and order sequence for a production operation are determined (Lütke Entrup, 2005; Stadtler & Kilger, 2005). Additional factors determined by plans and schedules include which products to produce, which machines to make the products on, which machines to overload, when to schedule maintenance, and which demands to satisfy (Fordyce et al., 2015; Pinedo, 2009). Factors such as the complexity of the production process, the number of products being produced, and the variability of product demand all influence the planning and scheduling process.

Aspects of the baking industry that complicate production scheduling are the multi-stage fermentation process, the presence of active yeast in the dough, handling of allergens and organic ingredients, and the use of large, capital-intensive production equipment which often requires lengthy setup times (Akkerman & Van Donk, 2009a; Modal & Datta, 2008). Additionally, production scheduling can be a cost driver for a company if the batch sizes, sequencing and finishing times are not optimal. Due to the broad range of effects of
planning and scheduling on overall business performance and given the increasing demand for flexibility from customers, research around scheduling in the baking industry is needed to help baked goods manufacturers gain and maintain a competitive advantage.

The food industry is an essential component of the European and global economies, accounting for roughly 13% of the turnover in the manufacturing sector in the EU in 2014 (Statistical Office of European Communities, 2017). Manufacturers of baked or farinaceous products are one of the principle niches within the broader food industry and have shown steady growth in revenue since 2010 in major European markets such as Germany (12%) and Italy (8%) (Statistical Office of European Communities, 2017). Despite this, the academic literature offers limited research on scheduling methods within the food sector and, more specifically, the baking industry.

When discussing the industrial landscape of Europe, it is necessary to consider small to medium-sized enterprises (SMEs) which employ fewer than 250 people and, yet, account for over 99% of the number of enterprises, 57% of total value added, and over 66% of employment in the EU (European Commission, 2016). SMEs in the food sector require a different approach for operations management due to the capabilities of management and limited resources (Dora & Gellynck, 2015; Rymaszewska, 2014). However, scheduling tools discussed in the literature have primarily catered towards large enterprises, focusing on the installation of software systems and optimisation models and algorithms (Van Donk & Van Dam, 1994), both options which can be out of reach for an SME in the baking industry.

This article, therefore, addresses the following research question: how can scheduling techniques be applied to improve production in the baking industry? This question is explored using a literature review of planning and scheduling methods in various food contexts, including baked goods manufacturing. Next, the product wheel methodology of King (2009) is selected for application and testing at a small to medium-sized baked goods manufacturer. The product wheel is a heuristic method for gaining economies of repetition while simultaneously responding to needs for increased variety and flexibility towards the end customer (King, 2009; Wilson & Ali, 2014).

This paper contributes to research by testing the product wheel in a food context, an industry with a documented need for better scheduling and which to date as seen limited research (O’Reilly et al., 2015). The paper contributes to practice by using a real-life case, hence illustrating the practicability of the approach.

The paper is structured as follows: first, a literature review is carried out exploring the baking industry, food sector, and scheduling methods. Second, the research methodology and empirical data are described. Third, the findings from the case study are analysed and theoretical and practical implications are described. Finally, conclusions and notes regarding further research are outlined.

2 Literature Review

A preliminary look at the literature revealed an absence of studies focusing on scheduling in the baking industry. Therefore, the literature search was expanded to explore scheduling methods in the broader food industry.

2.1 Baked Goods Manufacturing

Manufacturers of baked goods make products such as bread, cakes, and pastries that are baked in an oven (Oxford Dictionaries, 2015). Baked goods manufacturers can vary from large-scale to small-scale and may deliver either fresh or frozen products. Fresh bread products typically are provided to markets daily to ensure the product is of the acceptable quality level when purchased (Zhou & Therdtthai, 2006) while frozen products are often held in cold storage and delivered with longer lead times (Ribotta et al., 2006). These manufacturers may also make semi-processed baked goods such as refrigerated dough, frozen dough, and partially baked dough (Ribotta et al., 2006). A yeast bread-making process typically consists of the following stages: dough making,
dividing, proving, baking, cooling, slicing, and packaging (Zhou & Therdthai, 2006). Characteristic production systems for baking and other food processes are flow shops, a configured set of dedicated machines which process all jobs in a fixed order (Dewa et al., 2013; Gupta & Kumar, 2016).

2.2 Scheduling in the Food Industry

The current needs of the market and technological constraints of food manufacturers require production planners to consider several factors when scheduling jobs in production. These factors include the use of both batch and continuous processes within one production line, processing of perishable goods, sequence-dependent setup times, and high variability of yields and process duration (Akkerman & Van Donk, 2009b). For the larger context of consumer goods manufacturers, recent trends in operational scheduling have included grouping products into families which use a comparable production setup, the use of regular production schedules for high running products to increase customer responsiveness, the changeover time can be defined as the time needed to transition from producing one product to another. Often, changeover time includes the time to turn the line on or off, time for the system to adjust to temperature or pressure, and time to remove material from a previous production run (King, 2009). Changing between products on a manufacturing line. From a cost perspective, changeovers should be as short and infrequent as possible since they pose a significant cost for companies in waste product generated and reduced speeds during the start-up phase of a new product (Akkerman & Van Donk, 2008).

One method used in the food industry to improve mix flexibility is natural sequencing, a technique where similar products are scheduled in succession to minimise overall changeover time (Bilgen & Günther, 2010). When applying natural sequencing, sequences of products are often developed based on product families and consolidated into schedule blocks which are then arranged to minimise changeover time. A product wheel, like a schedule block, is a method for natural sequencing which uses a flexible scheduling sequence for production that is based on demand, changeover times, production rates, and inventory carrying costs (King, 2009). Product wheels can also serve
as a tool for continuous improvement whereby reducing the duration (or lot size) of a product wheel allows greater flexibility and responsiveness to customers (King, 2009).

2.4 Existing Scheduling Models for the Food Industry

Several operations research models and heuristics have been generated for specific food production industries, including the baking industry, as shown in Table 1. Since there were limited articles on planning problems in the baking industry, the literature search was expanded for those involving a food industry application. Food process applications represented among these models range from producing candy to baked goods to beverages. Different modelling formulations in the literature describe the specific production systems which vary depending on the number of production stages, the number and size of inventory locations, the presence of bottleneck resources, as well as the perishability of the products made. One model by Hecker et al. (2013) includes a no-wait constraint for a baked good production line to model the time-sensitivity of the fermentation process. This model was the only one to incorporate such a constraint specifically for the baking industry.

2.5 Literature Summary

This literature review shows that scheduling in the food industry is challenging and requires consideration of several factors. Furthermore, it shows that research into planning and scheduling in the baking industry is limited. The models currently developed and in use within the food industry are operations research models, heuristics, and lean scheduling methods, such as the product wheel. These models and tools vary depending on the nature of the production system being scheduled and are often customised to incorporate the specific constraints facing the food industry, such as perishability of the products and sequence-dependent changeover time.

This literature review reveals a lack of literature exploring both the quantitative and qualitative aspects of scheduling in the baking industry. There are limited applications of quantitative scheduling models made for the baking companies, with only three instances identified in Table 1. Also, lacking in the literature was the application of the heuristic methods, the product wheel more specifically, within the baking industry. Given the limited work in the food industry to meet the needs of food SMEs in Europe, the product wheel heuristic is selected for application in this study. This heuristic approach offers an approach to improve scheduling that is within the resources of a typical SME and accommodating the product mix flexibility required in the baking industry. The contribution of this paper is a map of literature on the scheduling practices and research in food companies as well as a real case application.

3 Methodology

A mixed methods approach was used to frame the empirical study of how scheduling methods can optimise performance in the baking industry. Both qualitative data and quantitative data were gathered from a case company to understand the scheduling process, schedule performance and productivity. Different data sources were also used for triangulation purposes. The explorative nature of the research question allows for an in-depth understanding of the research area, suitable for the qualitative work in this project, while the performance of the scheduling methods can be assessed using quantitative methods (Creswell, 2014).

The case company, here called Baking Company, is an SME located in Denmark with approximately 200 full-time employees. The company was selected as it produces a wide range of baked goods with over 200 products serving the convenience bread market (also known as “bake-off” market). Baking Company qualifies as being an SME per the definition of the European Commission (European Commission, 2016). All products are either fully baked or partially baked in the process and all are frozen before being sold. The company was also selected as their production
### Table 1. Operations Research Models and heuristics for Scheduling in the Food Industry

<table>
<thead>
<tr>
<th>Author</th>
<th>Model and Objective</th>
<th>Case</th>
<th>Solution Method and Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Silva, et al. (2014)</td>
<td>Model a flow-shop problem with parallel production, setup times, batch production, due date and include transport capacity.</td>
<td>Baking company</td>
<td>Apply a greedy heuristic and genetic algorithm to solve the problem.</td>
</tr>
<tr>
<td>Hecker et al. (2013)</td>
<td>MILP for Hybrid flow-shop. Uses no-wait constraints to model time-sensitivity with dough fermentation. Objective: Min. total makespan or idle time.</td>
<td>Bakery (Germany)</td>
<td>Solve for local optimal (not global) using Particle Swarm Theory and Ant Colony Optimisation programmed in MATLAB.</td>
</tr>
<tr>
<td>Dewa et al. (2013)</td>
<td>Finite capacity scheduling system applied to flow shop tested with 5 heuristics. Objective: Min. cost of earliness &amp; lateness.</td>
<td>Bakery (Zimbabwe)</td>
<td>Simulate 5 heuristics in Arena including Earliest Due Date, First Come First Served, First In System Last Served, Shortest Processing Time First, and a random procedure. EDD heuristic gave the optimal schedule.</td>
</tr>
<tr>
<td>Mehrotra et al. (2011)</td>
<td>MILP for creating production patterns in the processed food industry. Objective: Minimise setup and inventory costs.</td>
<td>ConAgra Foods</td>
<td>Two-stage heuristic which groups and assigns products to lines and sets sequence of each group. Use a heuristic-based planning tool which reduces the cost of setup and inventory by 15% with a 4-week long cyclic schedule.</td>
</tr>
<tr>
<td>Bilgen &amp; Günther (2010)</td>
<td>MILP applied to multi-site production and distribution. Objective: Minimise setup, inventory and transportation costs.</td>
<td>Fruit juice, 3 plants (Germany)</td>
<td>Uses block planning to model natural sequencing of products using randomly generated demand data. Solve models to optimality.</td>
</tr>
<tr>
<td>Christou et al. (2007)</td>
<td>IP with 3 levels of scheduling granularity for aggregate planning on multi-product lines. Objectives: maximise customer service level and minimise extra labour costs and inventory costs (maximise freshness).</td>
<td>Beverage manufacturer with 3 plants (Greece)</td>
<td>Solve to optimality using LP relaxation and a custom two-part optimisation for solving the shift allocation first and the scheduling second. Code programmed in ANSI.</td>
</tr>
<tr>
<td>Doganis &amp; Sarimveis (2007)</td>
<td>MILP to optimise production, customised for sequencing of yoghurt products. Objective: Minimise changeover, inventory, and labour costs.</td>
<td>Yoghurt production line (Greece)</td>
<td>Solve MILP using CPLEX to global optimality in less than 15 seconds. The output is a daily production schedule and resulting inventory levels.</td>
</tr>
<tr>
<td>Mendez &amp; Cerdà (2002)</td>
<td>MILP application to two-stage make-and-pack production with unlimited intermediate and final storage. Objective: Minimise total makespan.</td>
<td>Candy producer (theoretical)</td>
<td>Solved to optimality using CPLEX. Applied preordering rules (e.g. Shortest Intermediate Processing Time; General First Processed First Served) to reduce problem size.</td>
</tr>
<tr>
<td>Tadei et al. (1995)</td>
<td>Two model approach: (1) Medium planning using an LP to allocate labour and (2) short-term planning using an IP to determine shift schedule. Objectives: Min. inventory, meet demand.</td>
<td>Alimentary preserves (Portugal)</td>
<td>Solve using a decomposition heuristic was implemented using C++. The method proved as a consistent tool to evaluate what-if scenarios. Evaluate schedules based on average stock levels.</td>
</tr>
<tr>
<td>Randhawa et al. (1994)</td>
<td>Scheduling heuristic for a multi-stage system with parallel machines. Uses Shortest Processing Time First on bottleneck resources. Objective: Min. average flow times/lateness.</td>
<td>Freeze-dried food producer (USA)</td>
<td>Solve with a computer model which creates a schedule for each stage along with KPIs (% utilisation, % idle time, time in the system, etc.)</td>
</tr>
<tr>
<td>Claassen &amp; Van Beek (1993)</td>
<td>MILP model with two tiers (tactical and operational planning) applied to a flow shop with n-jobs and m-machines. Objective: Minimise penalty for lateness, setup, overtime, and costs.</td>
<td>Packaging line (Netherlands)</td>
<td>Solved to local optimality using a decomposition heuristic. Implemented programs into a decision support tool which generated higher quality schedules than the manually generated ones.</td>
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*Integer Programming (IP) using only integer variables, Linear Programming (LP) uses continuous variables, and Mixed-Integer Linear Programming (MILP) which uses both integer and continuous variables.*
system was seen to be typical for the baking industry, consisting of two automated, flexible flow shop production lines.

Based on the research question and findings from the literature review, a research framework was taken from the product wheel heuristic from King (2009). The method includes 10 steps which assess various aspects of the production system and scheduling practices. The steps are:

1. Decide which assets would benefit from product wheels.
2. Analyse product demand variability.
3. Determine the optimum production sequence.
4. Calculate the shortest wheel time based on time available for changeovers.
5. Estimate the economic optimum wheel time based on Economic Lot Size (ELS) model.
6. Determine the basic wheel time and determine which products are made on every cycle and the frequency for other products.
7. Calculate inventory levels to support the wheel.
8. Repeat Steps 3-7 to fine-tune the design.
9. Revise all scheduling processes, as appropriate.
10. Create a visual display (heijunka) to manage the levelled production.

These steps are shown graphically in Figure 1. Steps 1 to 7 of the method will be applied to the data set from one production line at Baking Company and the appropriateness of the approach will be assessed. The high-volume production line was selected as it is the production line with the highest capacity and is often running at full utilisation, therefore showing potential to benefit from further optimised production planning.

The primary methods of data collection were company visits, interviews, presentations by the senior staff, product documentation, sales records, and data from the manufacturing execution system. Production data used to create the product wheels is from the full year 2014. The product wheels generated will be tested using a simulation built in Microsoft Excel and four months of actual sales data from 2014 to see the impact on delivery service to the customers. The effect of the product wheel on delivery service to customers was measured as days with stock outs per product.

![Diagram of the product wheel method](image-url)

**Figure 1. Steps in the product wheel method.**
Adapted from (King, 2009)

Two days were spent on site in production observing the system and gaining an understanding of the process flow. During these visits, the production manager was interviewed for 30 minutes to understand the production data. Qualitative data on the planning process was gathered through two, one-hour semi-structured interviews with the
production planner to gain deeper insight and supplement the quantitative data. The questions focused on how schedules were created, rules for production sequence, and interactions between the planner and production team when creating the schedule.

The proposed research methodology allows for exploration of the gap in the literature regarding the impact of the scheduling via the product wheel in an SME in the food industry by using quantitative methods such as the ELS model and production cycles. The qualitative aspects are addressed by analysing the scheduling process of the production planner. This research methodology will also address the lack of the application of the heuristic scheduling methods within the baking industry with the development of production cycles at the case company.

4 Findings

Observations collected during the on-site visits at Baking Company revealed that the company uses a batch production system that is available for production approximately 90 hours per week, operating from Monday to Friday (i.e. maintenance time excluded). The product assortment at Baking Company consists of six major product groups: sausage rolls, Danish pastries, focaccia bread, buttermilk horns, pastry bars, and pastry rolls. Each product is assigned to a specific line for production as the preferred line. The production line selected for study produces mainly sausage rolls and buttermilk horns. All products at Baking Company are frozen and then baked at the retail location for final sale.

Figure 2 shows the primary process stages on the line. In mixing phase, the wet and dry ingredients for the dough are weighed and mixed. The mixed dough is then placed into a hopper and guided through an extruder and onto a conveyor to the lamination stage where the dough is rolled flat and layered. After lamination, the dough moves via conveyor to the makeup stage where it is cut and formed into the final shape with additional ingredients, such as sausages, cheese, and cream filling. The formed products are placed on trays and then moved to a proofing step where the dough can rise before either being frozen or baked. The products which are fully or partially-baked can cool before being frozen. Once frozen, all products are placed in boxes and palletised before moving into cold storage. The products have a one-year shelf-life in cold storage.

4.1 Creating the Master Production Schedule

To assess the qualitative nature of the planning tasks, a task decomposition of the production scheduling process at Baking Company was created. At the highest planning level, a master production schedule (MPS) is created by the production planner which shows the aggregated volumes of each product to be produced on both lines. Each week, the production planner develops the MPS for a six-week planning horizon and then revises it based on rush orders and orders for MTO products. MTS products are selected for production based on their inventory levels and expected demand. MTO products are scheduled with a lead time of 3-4 weeks while MTS products must be delivered in one day due to the competitive nature of the convenience bread market. With such short lead times, the MTS products must have a sufficient stock level to cover demand with an acceptable level of service.

4.2 Creating the Detailed Schedule

Once the aggregate planning values are determined in the MPS, the planner generates the detailed production schedule with a one-week planning horizon. A minimum run length is set to 3 hours and a target run length is 7.5 hours, which is the approximate length of one shift. The planner uses a combination of rules of thumb along with
the planning interface of the ERP system to determine the run length and achieve the desired volume in the MPS. Once the planner determines the run lengths, she assigns the products to the line, sequences the products based on scheduling rules and then estimates the changeover time. These tasks are often executed in parallel as the planner attempts to make the schedule fit demand while complying with capacity constraints.

As is common in the food industry, many planning rules are used to create schedules for Baking Company to reduce production costs. The following list contains a set of planning rules that are currently used at Baking Company to form the MPS and the detailed production schedule:

- Organic items are scheduled as the first of the week to avoid contamination.
- Light-coloured doughs are scheduled before dark-coloured doughs to avoid colour mixing.
- Items with sauce are scheduled after items without sauce and toward the end of the week to avoid excessive cleaning.
- Products with allergens (i.e. sesame or almonds) are run as the last product for the week.
- Fully-baked products are scheduled separately from partially-baked products.
- Chicken products are always made before pork products to reduce the risk of cross-contamination.

Once the schedule is made for the week, the planner reviews the schedule with the production team leader for feasibility. The planner requests feedback on the planned changeover time, sequencing, time for new products, and other factors before updating the schedule and releasing it to production. During on-site visits, it was seen that the production planner at Baking Company maintains daily communication with the production workers and is seated in an office that is close to the factory operations.

4.3 Production Volume

A Pareto method called the Glenday Sieve was applied to production data with a summary shown in Table 2 to visualise the distribution of the production volume among the products at Baking Company (Glenday, 2005). The Glenday Sieve reveals that half of the production time was spent making only 19 products on both lines at Baking Company in 2014. These represent the high running products such as a Danish pastry product and various products from the sausage roll group. The Glenday Sieve also shows that 27 products contribute to the red category which accounts for only 1% of production time at the facility. With the highest concentration of stock keeping units (SKUs) residing in the yellow group, it appears that the company is spending 95% of its time making only 65% products. The Glenday Sieve reveals a clear distinction between the products that are “high runners” and those that are “low runners” at Baking Company. Furthermore, the production time is unevenly distributed amongst the products with a moderately long tail taking only limited capacity.

<table>
<thead>
<tr>
<th>Product Colour</th>
<th>Cumulative % Production Hrs</th>
<th>Number of Products</th>
<th>% of Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>50%</td>
<td>19</td>
<td>12%</td>
</tr>
<tr>
<td>Yellow</td>
<td>95%</td>
<td>88</td>
<td>53%</td>
</tr>
<tr>
<td>Blue</td>
<td>99%</td>
<td>31</td>
<td>19%</td>
</tr>
<tr>
<td>Red</td>
<td>100%</td>
<td>27</td>
<td>16%</td>
</tr>
<tr>
<td>Total</td>
<td>100%</td>
<td>166</td>
<td>100%</td>
</tr>
</tbody>
</table>

5 Analysis

In the following sections, the first seven steps of the heuristic presented by King (2009) is applied to the 2014 production and sales data to test the applicability of the method to the baking sector. The details of the implementation are listed in the following sections.

1. Decide which assets would benefit from product wheels.
The asset at the Baking Company selected for study is a high-volume, flow shop production line (Gupta & Kumar, 2016). The production line is scheduled as a single unit since all machines connect via a conveyor system with low work in process inventory between machines.

2. Analyse product demand variability.

An analysis of the variation of monthly demand for a full year of sales data from 2014 was performed for products at Baking Company based the method of D’Alessandro and Beveja (2000). In this method, the average monthly demand and coefficient of variation (CV) of monthly demand are calculated for 86 products produced on the line and graphed to segregate the products into MTO and MTS categories. The findings for Baking Company are presented in Figure 3.

![Figure 3 Analysis of the Variation of Monthly Demand (Logarithmic Scale with Quadrants)](image)

The threshold CV value was set to 1.0 since most of the green and yellow products (high volume products from the Glenday Sieve) had CV values between 0 and 1.0. The threshold value for average monthly demand was set to 300 cartons as this equates to roughly one 3-hour production run every two months for most products. As 3 hours is the minimum run length in production, making this quantity every two months was deemed to be “low running.”

As is typical for this demand analysis, the products in Q2 are classified as MTO, and the products in Q4 are classified as MTS. The products in Q1 and Q3 can be classified as either MTO or MTS depending on the company sales and operations strategy. In this analysis, the Q1 and Q3 products are designated as MTS as the frozen nature of the food allows them to stay in inventory with a low risk of being scrapped. Table 6 shows a summary of the four quadrants including the number of products within each and strategies for scheduling them, where 81 of the 86 products classify as MTS. The 81 MTS products will be carried through the remaining steps of the product wheel heuristic since the 5 MTO products should be scheduled only when an order is received.

When comparing the results of the Glenday Sieve to the results of the demand variability analysis, all green products from the Glenday Sieve were designated as MTS based on the demand variability analysis as they fell within Q4 (high volume, low demand variability).

<table>
<thead>
<tr>
<th>Table 3. MTO and MTS Segregation for Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q2 – Low volume, high variability</td>
</tr>
<tr>
<td>Strategy = MTO</td>
</tr>
<tr>
<td># Products = 5</td>
</tr>
<tr>
<td>Q1 – High volume, high variability</td>
</tr>
<tr>
<td>Strategy = MTS</td>
</tr>
<tr>
<td># Products = 4</td>
</tr>
<tr>
<td>Q3 – Low volume, low variability</td>
</tr>
<tr>
<td>Strategy = MTS</td>
</tr>
<tr>
<td># Products = 26</td>
</tr>
<tr>
<td>Q4 – High volume, low variability</td>
</tr>
<tr>
<td>Strategy = MTS</td>
</tr>
<tr>
<td># Products = 51</td>
</tr>
</tbody>
</table>

3. Determine the optimum production sequence.

Using the 81 MTS products as a basis and the scheduling rules gathered from the interviews production planner, the optimal production sequence was determined. The data from the interview was triangulated by an assessment of the planned changeover time between the product groups in 2014 since changeovers at Baking Company are sequence-dependent. A changeover time matrix was made on the product level but was not utilised since there were many missing combinations of products; therefore, the average changeover time between product groups was used. Both analyses showed that changeover time is minimised when scheduling items from the same product group next to each other.

4. Calculate the shortest wheel time based on time available for changeovers.
This step advises the user to place all products in a single production cycle and estimate the number times a changeover could be performed. Using equation (1) presented by King (2009), the maximum number of cycles of a product wheel in one year which contains all MTS products for the line is computed as 1.7 (see equation 2). This is calculated assuming the total available production time on the line is 4,320 hours (90 hours per week, 48 weeks per year), the total production time equals the production time from 2014 for the MTS products and that the product wheel changeover time is the sum of the average changeover time for the MTS products. The calculation shows that the production cycle should be run between one and two times every year if all products are made once in every cycle.

\[
\text{Max Cycles} = \frac{\text{Total Avail. Time} - \text{Product Wheel Time}}{\text{Product Wheel Changeover time}}
\]

\[
\text{Max Cycles} = \frac{(4320 - 4232)}{53} = 1.7
\]

5. Estimate the economic optimum wheel time based on ELS model.

Continuing with the product wheel heuristic, the Economic Lot Sizing (ELS) analysis was performed to calculate the optimal batch sizes for production of the 81 MTS products on the line at Baking Company. The ELS calculates the cycle length \( x_j \) (the amount of time between production runs for each product \( j \)) and the lot size. Variables in the calculation were determined using the sales and production data from 2014. The inventory holding cost, \( h_j \), was determined by taking the costs per carton for storage and handling finished goods at an external warehouse close to Baking Company. The calculation of lot size (cycle length multiplied by demand rate) is shown in equation 3 where:

\( j = \) product number

\[ ELS_j = x_j D_j = \sqrt{\frac{2Q_j c_j}{h_j (1 - \frac{Q_j}{D_j})}} \] (3)

For each product, the optimal run length, lot size and production frequency were determined. The base units for volume and time in this analysis are cartons and hours. This model assumes a constant demand rate and production rate and utilises sequence-independent setup times in the calculations. While the production at the Baking Company experiences sequence-dependent setup times, the sequence-independent setup time was calculated by taking the average setup time for each product to simplify the model. Three of the MTS products had cycle lengths greater than once every year, which is not feasible given the one-year shelf-life of the products.

6. Determine the basic wheel time; determine which products are made on every cycle and the frequency for others.

Since there were 81 MTS products, a different strategy for generating production cycles was required. The basic wheel time is usually set by the high-volume products (King, 2009). A histogram of the cycle lengths for the line studied (see Figure 4) shows that most products have a 5-6-week cycle length, while most products have a cycle length of less than 11 weeks. No products had a cycle length less than 3 weeks. High volume, green products have cycle lengths from the ELS analysis which ranged from 3.3 – 6.2 weeks.
For the first iteration, the product wheel uses a 4-week cycle time which repeats two times so that products are made every 4 or 8 weeks while other MTS products are made when the stock is nearly depleted. All product cycle lengths were rounded to the nearest multiple of four, and the lots sizes were updated. The product wheels generated are shown in Figure 5 and Figure 6. The green and yellow colours in the figures indicate the colour classification per the Glenday Sieve and serve as a reference for the high volume and mid-volume products.

Figure 5. Product Wheel for weeks 1-4

The wheels were designed so that the product cycle always takes 70% of the production time for the week to allow room in the schedule for MTO products which have a lead time of 3-4 weeks. As suggested by King (2009), products which have a cycle length over eight weeks should be placed in empty grey spokes to accommodate both MTS and MTO production strategies. Only 35 products with an MTS strategy which had cycle lengths of less than eight weeks were included in the product wheel. Since products made every 12 or more weeks are made only 5 or fewer times per year, these are not included in the product wheel but are given space to be produced in time designated for “Other Sausage Rolls”, etc. shown as one of the grey spokes in the wheels in Figures 5 and 6.

Figure 6. Product Wheel for weeks 5-8

7. Calculate inventory levels to support the wheel.

For testing the production plan, the safety stock levels were set at two weeks of the product demand which is the current safety stock target for high running products at Baking Company. Simulating the product wheels with actual demand data for four months (March 3, 2014 – June 25, 2014) at Baking Company was possible for the 32 products which were in the product wheel. Demand data was not available for three of the products in this time frame, so only 32 of the 35 products were assessed. The simulation demand period was selected to minimise the influence of seasonality in demand. In the simulation, stocks were initialised to be equal to the economic lot size plus the safety stock for each product. For each day in the simulation, the production quantities from the product wheels and demand quantities from the demand data were added or deducted from the stock in the previous day accordingly for each product.
The simulation of the first version of the product wheel showed that two products faced stock-outs over the four-month period: Scones G has 13 days without stock and Sandwich R has two days without stock. The lot sizes were increased and the simulation ran a second time where there were no stock-outs.

6 Results and Discussion

It is estimated that implementing the product wheels will lead to a 42-hour reduction (-18%) in changeover time on the line, which equates to roughly 2 days of additional production time per year. The impact of the product wheel on setup and inventory costs is also found and summarised in Table 3. As can be seen, implementing production cycles could potentially lead to EUR 103,600 (23%) decrease in annual setup and inventory costs from 2014. As this applies to the products that are already running in long production series, some of the benefits are overlooked. For example, if all products are scheduled in economic lot sizes, the company could potentially save EUR 145,000 in costs. Such results show that this manual heuristic did accommodate the need for mix flexibility and minimisation of production costs in Baking Company.

Table 3. Impact of the product wheel on annual setup and inventory costs for 35 MTS products

<table>
<thead>
<tr>
<th>Changeover Cost (EUR)</th>
<th>Inventory Holding Cost* (EUR)</th>
<th>Total (EUR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Schedule (2014)</td>
<td>226,400</td>
<td>217,100</td>
</tr>
<tr>
<td>Product Wheel</td>
<td>180,200</td>
<td>149,000</td>
</tr>
<tr>
<td>Savings</td>
<td>46,200</td>
<td>57,400</td>
</tr>
</tbody>
</table>

* Inventory cost includes the cost of safety stock

Note: costs and savings calculated only for the 35 products assessed in the product wheel.

The theoretical savings calculated for the production cycles at Baking Company are slightly higher than other research studies which used production cycles, such as the 15% reduction in setup and inventory costs found by Mehrotra et al. (2011) using their optimisation model. A study of product wheels in the process industry showed mixed results as to the impact of scheduling on changeover time, increasing the time in some cases and decreasing time in others (Wilson & Ali, 2014).

Where the product wheel had less favourable results in the case application was in the meeting demand requirements to the market for the MTS products. The lack of widespread stock-outs suggests that the inventory levels and batch sizes can be reduced slightly, but seasonality of demand should be considered. The stock out situation of Baking Company is comparable to the product wheel implementation at a chemical manufacturer (Wilson & Ali, 2014). It is worth noting that while making the product wheels in a real production scheduling scenario, the stock levels and corresponding lot sizes would need to be adjusted per the changing market needs and demand seasonality. However, the sequence of the production runs should remain the same since it is designed to reduce the total changeover time and inventory costs based on natural sequencing.

Looking beyond the production and warehouse impact, implementing the production cycles at the case in this study requires changes to the scheduling process, as well. In one potential redesign of the process, the product wheels are the first items to be planned when creating the MPS. The cycles are allocated across the weeks and production lines based on their cycle length. If there is capacity remaining in each week after production cycles have been allocated, the items are selected for production based on the original process. This process is expected to reduce the decision-making load of the planner.

The specific heuristic presented by King (2009) was difficult to apply to the case company for various reasons. The presence of sequence-dependent changeover times made the manual tasks in Step 3 of determining the optimum production sequence quite tricky. Step 4 of calculating the shortest wheel time was not readily applicable given the high product variety of the 81 MTS products. The heuristic assumes that all products are made in every cycle, which would mean that a
A production cycle would be developed for up to 81 products which would be scheduled over the course of 5-6 months, compared to the 35 products in the proposed 8-week product wheel set. This would be complicated and reduce the chances that the benefits of the product wheel, such as economies of repetition and making faster changeovers in production, would be realised. Running a production cycle twice per year will pose many practical challenges, such as very high batch sizes and stock levels for products. This shows that the product wheel method is not the best fit for production scenarios in the process industry which have a high number of MTS products. In a study on product wheels at a chemical manufacturer, only eight products were included in the product wheel design, so this was much simpler to generate the schedule for (Wilson & Ali, 2014). This suggests that the product wheel is more suitable for smaller scheduling problems.

Among the collection of scheduling methods tested in the food sector, the product wheel is an overly simplistic approach for the high variety company which was studied in this case. The product wheel offered an approach by which variety and sequencing could be addressed in the scheduling process in the baking company. However, based on the application example of Baking Company in this study, it can be concluded that the method should be reserved for small problems where few MTS items are required to be integrated into the product wheel. The other optimization models presented in Table 1 which utilised operations research methods to solve the issues of natural sequencing via schedule blocks might be more suitable for solving applications with higher variety (Bilgen & Günther, 2010; Günther et al., 2006; Mehrotra et al., 2011; Mendez & Cerdá, 2002; Pinedo, 2009). Just like the product wheel, the operations research production cycles aim to increase production efficiency by using pre-defined sequences of production orders. However, their solving ability for more complex problems makes them superior to the product wheel. Regardless of the issues with implementation, the simulation of the product wheel at Baking Company showed savings in changeover and inventory costs.

7 Conclusions and Future Research

Through a literature review and application of the product wheel methodology to a case company, it was found that the production cycles are a suitable scheduling method for improving the production performance in the baking industry, particularly at small to medium-sized enterprises. However, when testing the product wheel method proposed by King (2009) at a case company with high product variety, the method was found difficult to apply due to its manual nature. The results suggest that when scheduling production in a baking company with high variety, a more sophisticated technique for scheduling based on operations research methods should be utilised. Despite the drawbacks with the number of products, the product wheels generated in the study led to a 23% reduction in changeover and inventory costs for the products simulated at the case company.

This work contributes to the current gap in the literature aspects of scheduling in the baking industry by providing a case-based approach to show the applicability of production cycles as a scheduling method to a baked goods manufacturer and significant benefits of production cycles in this sector are estimated. This research study is limited in generalizability due to the nature of the case study. However, it is reasonable to assume that applying the product wheel in another food company with similar variety and seasonality would yield comparable results. The primary area of future work is to implement and assess the effectiveness of the proposed production cycles. Such research would provide the data needed to evaluate the actual performance of the cycles against the estimated performance and compare them to the simulated values.
References


