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Processes and optimization approaches for integrated strategic planning of operations at automotive manufacturers: Impact of product platforms and modularization

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Abstract

Automotive manufacturers have introduced product platforms and modularization as mitigation strategies for the recent industry developments. As a result, significant changes in planning processes and optimization are required. This thesis addresses three topics in the field of automotive operations management, which support this transition. The first topic defines a comprehensive framework, while the second and third topic consider selected decision problems in the defined framework.

The first topic focuses on integrated business planning at automotive manufacturers. Integrated business planning aims at an alignment of design projects with cyclic planning processes. We propose a reference process for integrated business planning at car manufacturers and identify the integration challenges. We find several shortcomings in addressing the integration challenges in industrial practice. Furthermore, we provide a structured review of academic optimization approaches that support the integration challenges and identify several directions for future research.

The second topic considers time-phased capacity planning under uncertain demand forecasts. Due to long and diverse lead times of the equipment, manufacturers have to make time-phased decisions about capacity configurations based on regularly updated demand forecasts. We provide an innovative optimization approach based on a Markov decision process employing Bayesian updating. To consider risk attitudes, we adapt the decomposition theorem of the conditional value at risk. We prove our approach's superiority. We determine the performance loss caused by the wide-spread practice of central capacity fixing and of the flexible body shops enabled by modularization.

The third topic focuses on dynamic platform planning under uncertain technological innovations. When manufacturers launch a new platform, the timing determines the trade-off between the platform's technology level and the time available for product development. We introduce a stylized model based on a stochastic process for capturing the uncertainty of innovations. We prove that the optimal policy for the platform launch is a time-dependent threshold of the observed innovation level. We find that manufacturers can suffer a loss of flexibility that significantly reduces platform benefits.

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Acronyms

2SP	Two-stage Stochastic Programming with recourse (risk-neutral).
2SPR	Two-stage Stochastic Programming with recourse (Risk-averse).
AP	Allocation Planning.
B	Benchmark model (risk-neutral).
BoM	Bill of Materials.
BP	Budget Planning.
BR	Benchmark model (Risk-averse).
BTO	Built To Order.
CF	Central capacity Fixing.
CKD	Completely Knocked Down.
CPM	Capacity Planning Model.
CPMR	Capacity Planning Model considering Risk.
CSP	Component Supply Planning.
CVaR	Conditional Value at Risk.
DOP	Day Of Production.
JIS	Just In Sequence.
JIT	Just In Time.
LCM	LifeCycle Model.
MDP	Markov Decision Process.

MILP   Mixed-Integer Linear Program(ming).
MPP   Master Production Planning.
MPS   Master Production Scheduling.
MRA   Modular Rear-wheel drive Architecture.
MRP   Material Requirements Planning.

NCF   No Central capacity Fixing.
NPV   Net Present Value.

OEM   Original Equipment Manufacturer.
OP   Order Promising.
OR   Operations Research.

R&D   Research and Development.

S   Sequencing.
S&OP   Sales and Operations Planning.
SOP   Start Of Production.

VaR   Value at Risk.

Chapter 1.

Introduction

1.1. Motivation

The automotive industry is an important industry on a global scale. Global car sales were growing by 3.6 percent annually from 2010 to 2015 to reach a level of USD 2,750 billion. Driven by the performance in emerging countries such as China and India, sales are expected to continue growing by two percent annually until 2030 (McKinsey & Company, 2016). For some economies, the automotive industry represents the major driver of wealth and progress. In Germany, for example, the automotive industry counts as the largest industry sector with a total revenue of EUR 400 billion (around 20 percent of the total German industry revenue), research and development (R&D) expenditures of EUR 20 billion (35 percent of total German R&D expenditures), and 800,000 employees (Germany Trade & Invest, 2016).

However, despite their relevance and influence, automotive manufacturers currently compete in a challenging environment. The growing global demand for cars forces the manufacturers to invest in a global expansion of their production networks, in accordance with difficult boundaries such as local content requirements in emerging countries. At the same time, the customer requirements that automotive original equipment manufacturers (OEMs) have to fulfill, become more diversified due to both the expansion of the OEMs into new sales regions and the increasing demand of current customers for tailored products. Furthermore, the increased globalization in the automotive industry has led to heavy competition among the OEMs. As a result, margins have been shrinking, leading to a high cost pressure. Finally, the increased pace of technological development, for example driven by digitization and connectivity, has forced automotive manufacturers to shorten the length of product lifecycles, implying more frequent new product introductions.

To handle these challenges, automotive manufacturers have developed several mitigation strategies. Two important strategies among these are product platforms and vehicle modularization. A product platform is a set of core assets, e.g. components, interfaces, or technologies, that provides the technological foundation for multiple car models. Modularization describes the facilitation of common parts based on a component-specific strategy using standardized interfaces across all products of a manufacturer. Both are product design levers that aim at cost reductions and cross-product synergies such as increased design and process flexibility and process responsiveness. However, they directly influence planning boundaries and planning processes of the manufacturer.

Consequently, to realize savings and synergies resulting from product platforms and modularization, OEMs must restructure their planning processes and introduce dedicated optimization techniques. The planning processes have to be integrated, i.e. existing processes within functional areas must be linked to each other, interdependencies between products must be considered, and product ramp-ups must be systematically supported as part of the steady-state operations. Supporting tools based on state-of-the-art optimization approaches have to be built around these integrated processes to reflect the resulting interactions and interdependencies in the planning landscape. Thus, automotive manufacturers will see a competitive advantage or disadvantage, depending on how successful their processes and tools are adapted.

The research presented in this thesis aims at supporting automotive manufacturers in this transition. In the remainder of this chapter, we discuss the contribution and research objectives, introduce the specific research topics and the associated research questions, give a brief outline of the thesis, and provide a list of publications that are related to this thesis.

1.2. Research objectives

To support automotive manufacturers in integrated strategic planning of their operations, this thesis contributes to both the research on planning processes at automotive manufacturers and the research on optimization approaches to support these processes. Furthermore, it aims at bridging between these two research fields and at enhancing the correlation of academic research and industrial practice.

To reach this objective, the presented research focuses on three topics that build on each other. The first topic takes a comprehensive perspective and defines the framework for the second and third topic, which propose fundamental methodologies and deepen

the analysis in two selected areas.

The first topic analyzes the current state of planning processes at automotive manufacturers and of optimization approaches proposed by academic literature to support these processes. First, the investigation focuses on integrated planning in the context of product platforms and modularization. In particular, the challenges that result from integrating cyclic planning processes with planning processes for development or design projects are of interest. Therefore, in the second step, optimization approaches proposed by academic literature are analyzed with respect to these integration challenges.

Based on the derived research directions to support the identified integration challenges, two challenges are selected for detailed analysis, determining the second and third research topic. Both topics focus on a specific decision problem that is placed in the context of the selected challenge. Therefore, two optimization approaches are developed that address the characteristics required for integrating a strategic cyclic planning process with the planning of design projects. Furthermore, the product and process characteristics resulting from platforms and modularization are considered. Consequently, the proposed models can serve as prototypes for optimization approaches that aim at supporting other integration challenges.

In the following, we briefly introduce each topic and define the associated research question.

1.2.1. Integrated business planning

Based on the aforementioned need for integrated planning processes and the resulting requirements for optimization approaches, the first research topic is built around the concept of integrated business planning. Recently, integrated business planning has emerged to one of the key topics for practitioners in operations management, as publications of several consultancies show (e.g. Ernst & Young, 2015a; KPMG, 2014).

Processes for integrated business planning

The hierarchical planning landscape at automotive manufacturers is characterized by two types of processes, processes for design projects and cyclic processes. Cyclic processes on the strategic level, such as the recurring product planning process, define the long-term strategy of an OEM. Based on the planning outcome, design projects, for example as part of the new product development, are conducted to implement the defined strategy. These projects last several years and, finally, are fed into the cyclic processes on the tactical

level, which focus on the planning of operations for current products. Traditionally, most of these processes have been conducted separately focusing on a specific product.

However, due to the introduction of product platforms and modularization and due to the frequent new product introductions, a planning framework that systematically integrates these processes has become absolutely necessary. In industrial practice, the need for integrating the planning processes has been recognized over the last years and has led to the concept of integrated business planning. Without a structured process supporting integrated business planning, automotive manufacturers risk to miss out on realizing the savings and synergies that should be facilitated by product platforms and modularization. Therefore, the first research question is formulated as follows:

Research Question 1.A. *How should the process for integrated business planning be defined for automotive manufacturers to systematically integrate cyclic planning with the planning of design projects? What are the challenges in integrated business planning and what is the state of the art in the industry?*

Optimization approaches for integrated business planning

To establish a structured and standardized process for integrated business planning, appropriate decision support is required. Thus, academic research focusing on optimization approaches for automotive manufacturers has to evolve in order to fulfill the requirements resulting from integrated business planning. For example, cross-functional interdependencies should be integrated and emphasized in decision support tools. Furthermore, the special characteristics in cyclic planning and in the planning of design projects should be considered.

Therefore, to bridge the gap between the research on planning processes and the research on optimization approaches with respect to integrated business planning, the following research question is studied:

Research Question 1.B. *To what extent do optimization approaches proposed in academic literature support integrated business planning and the corresponding integration challenges? What are the resulting priorities for future academic research?*

1.2.2. Time-phased capacity planning

The second topic of this thesis focuses on capacity planning projects for new car models and the challenge of integrating them with the cyclic demand planning process. Dealing

with the complexity of automotive operations and managing changes to demand are two of the key success factors in automotive capacity planning (Dharmani et al., 2015). Both are challenging due to the interdependencies between the car models and due to the high demand uncertainty.

The capacity projects focus on planning and constructing the facilities required for each stage in the automotive manufacturing process. Due to differences in construction and equipment procurement lead times, the decisions on the capacity level of each stage are distributed over several years. Furthermore, several stages in the manufacturing process are shared by car models with diverse start of productions (SOPs). The capacity planning problem hence consists of multiple, time-phased decisions for multiple products. Due to the high demand uncertainty, forecasts are updated regularly in a cyclic demand planning process. Thus, the time-phased decisions on the expensive manufacturing equipment must be made based on volatile demand information, implying a high investment risk.

In this context, two current observations can be made at OEMs. First, to prevent misalignment between the capacity configuration of the manufacturing stages, a pragmatic approach is followed by conducting an early central capacity fixing of all associated stages. Second, enabled by modularization, OEMs recently started to introduce flexible body shops that, in contrast to conventional body shops, are shared by multiple car models. Therefore, the following research question is analyzed:

Research Question 2. *How can interdependencies between the cyclic forecasting process and the capacity planning projects be systematically addressed? To what extent can investment risk be considered in the time-phased decision making? What is the impact of an early central capacity fixing and of flexible body shops enabled by modularization?*

1.2.3. Dynamic platform planning

The third topic analyzed in this thesis focuses on the planning of product platforms and the interdependencies with technology innovation projects and product design projects. Product platforms are a popular mitigation strategy to address the increasing demand for product variety in the automotive industry, while realizing cost savings and synergies in production and development. Providing the technological basis for all its derivatives, the platform enforces a joint technological solution. Customers, however, are sensitive to the platform-dependent technology level employed by their car, with expectations varying between product segments. Furthermore, the technology level of the platform

depends on innovations developed in R&D projects that are highly uncertain in terms of success and timing.

At some point in time, the manufacturer has to release the platform based on the available level of innovation to initiate the development projects for the platform's derivatives, referred to as the platform launch. Hence, the timing of the platform launch determines the technology level of all derivatives and therefore impacts the level of the innovation-sensitive customer demand. Furthermore, a platform's derivatives typically have diverse SOPs defined by a fixed schedule that is driven by customer expectations and competitor schedules. Thus, the timing of the platform launch also determines the time available for the individual product development projects and consequently affects the development costs (the shorter the development time, the higher the costs). The dynamic platform planning problem aims at solving the trade-off between a high technology level and a sufficient development time for platform-based products.

In this context, several cases of companies failing to successfully employ platforms have been observed, some even abandoning the platform concept (Boas et al., 2013). One of the reasons could be a loss of flexibility due to the compromise in timing and in level of innovation made by the manufacturer when determining the platform launch. Hence, the following research question is formulated:

Research Question 3. *How can the interdependency between the technology innovation projects and the platform planning process be analytically described? Can the optimal policy for the platform launch be characterized by structural properties? Are there considerable flexibility losses due to platforms?*

1.3. Outline of the thesis

This thesis is structured as follows. Chapter 2 focuses on Research Question 1.A. It reviews planning processes at automotive OEMs emphasizing the interaction of design projects with cyclic planning processes. We propose a reference process for integrated business planning at car manufacturers based on industry interviews and existing academic literature. Furthermore, we identify the resulting integration challenges that manufacturers currently face. We find that OEMs must establish a structured alignment mechanism between production and sourcing network design projects and cyclic sales and operations planning (S&OP) to increase the efficiency of production and supply chain ramp-ups. Furthermore, manufacturers must establish processes for integrating

project planning and cyclic planning for new and existing vehicle types to leverage the scale effects of the platform and module strategies.

Chapter 3 investigates Research Question 1.B. and analyzes operations research (OR) approaches proposed by academic research in a structured review, with respect to the reference process and the integration challenges described in Chapter 2. We find that the current literature lacks in the consideration of cross-functional interdependencies and disregards the distinctly different characteristics of project planning and cyclic planning.

Chapter 4 focuses on Research Question 2. It studies time-phased capacity planning for new car models. We identify the key interactions between the capacity planning projects and the cyclic forecasting process and provide an innovative planning approach based on a Markov decision process (MDP) employing Bayesian updating. To consider risk attitudes we extend the approach by employing the conditional value at risk (CVaR). We show the superiority of our approach over conventional stochastic approaches and determine the performance loss caused by the wide-spread practice of central capacity fixing. Furthermore, we find that flexible body shops facilitated by vehicle modularization come at hidden costs caused by the resulting loss of decision flexibility.

Chapter 5 investigates Research Question 3. It analyzes dynamic platform planning. We introduce a stylized optimization model for the dynamic platform planning problem based on an MDP capturing the uncertainty of technological innovations provided by R&D. We find that the optimal policy for the platform launch is a time-dependent threshold of the observed innovation level. Furthermore, we find that manufacturers suffer a loss of flexibility reducing the platform benefits. The loss depends on the product introduction schedule, the product heterogeneity, and the assignment of products to platforms.

Chapter 6 summarizes the findings with respect to the defined research questions, presents a synthesis, and gives an outlook.

1.4. Related publications

The research presented in this thesis is based on three individual papers that all have been submitted to selected journals. Each of the following chapters is based on the research paper indicated below. Thus, this thesis provides a consolidated view on processes and optimization approaches for integrated strategic planning of operations at automotive manufacturers.

Chapters 2 and 3

Jana, P. and M. Grunow (2018a). Integrated business planning in the automotive industry: Reference process and literature review. *Submitted for publication.*

Chapter 4

Jana, P. and M. Grunow (2018b). Time-phased capacity planning in the automotive industry. *Submitted for publication.*

Chapter 5

Jana, P., S. C. Graves, and M. Grunow (2018). Balancing benefits and flexibility losses in platform planning. *Submitted for publication.*

Chapter 2.

Integrated business planning in the automotive industry: A reference process

Integrated business planning aims at an alignment of development and design projects with cyclic planning processes. It is a core capability in the automotive sector, in which car manufacturers aim at integrating long-term projects for the design of new vehicle types, for the development of new process technologies, and for the redesign of production and sourcing networks with cyclic processes such as rolling-horizon S&OP and long-term product planning. Despite its increasing practical importance, integrated business planning has received little attention in academic literature. We therefore propose a reference process for integrated business planning at car manufacturers and identify the integration challenges. To derive the reference process, we combined an extensive review of academic literature on planning processes in the automotive industry with interviews at manufacturers. We find that automotive manufacturers must establish a structured alignment mechanism between network design projects and cyclic S&OP to increase the efficiency of ramp-ups. In addition, manufacturers must establish processes for integrating project planning and cyclic planning for new and existing vehicle types to leverage the scale effects of platform and module strategies.

2.1. Introduction

A distinction between two landscapes characterizes planning processes at automotive OEMs: Processes for design projects and processes for cyclic planning. OEMs have defined processes for three types of design projects: Product design to develop new vehicle types, process technology design to develop new manufacturing technologies, and network design and ramp-up to adapt the production and sourcing network for a new vehicle type. These tasks are organized as long-term projects with dedicated teams and a clearly defined end. In contrast, cyclic planning is performed in fixed cycles in a rolling-horizon planning scheme. In the long term, product planning reviews the product strategy to adapt the vehicle portfolio to recent market developments. Annual demand planning provides updates of the global long-term forecast. In the medium term, S&OP balances supply and demand for the existing vehicle types. Figure 2.1 shows the principle interaction between both landscapes. The strategies defined by long-term cyclic processes are implemented through the definition of design projects. The resulting designs in turn feed into the mid-term cyclic processes.
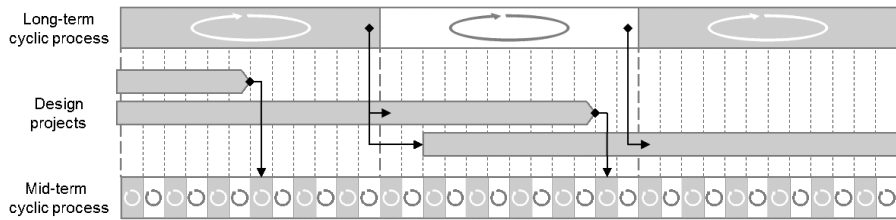
Figure 2.1: Simplified illustration of interactions between planning of design projects and cyclic planning processes.

Car manufacturers have moved from an integrated product design toward a platform-based and modular design. Today, they strive to realize the associated savings potential resulting from synergy and scale effects in development, production, and sourcing (El-Maraghy et al., 2013). For this purpose, planning must be performed across all vehicle types based on a platform or module, including existing and future vehicle types. Therefore, the product planning process, which defines the platform and module strategy, must not only provide a framework for the design projects of new vehicle types, but must also be aligned with the design of production and sourcing networks.

For each new vehicle type, the production and sourcing network design is adapted, the required production capacities and processes at the manufacturing sites are planned, and, finally, the production is ramped up. Integrating these projects into ongoing pro-

duction substantially increases the complexity of the planning processes. Furthermore, shorter lifecycles and broader product portfolios imply an increasing number of such development projects (Pil and Holweg, 2004). Hence, OEMs are consistently in a situation, where capacities for new vehicle types are being built or production is being ramped up. Together, the complexity and frequency of the design projects and their integration in cyclic planning pose a challenge for OEMs. The success of OEMs in addressing this challenge determines their ability to reduce time-to-market of new products and thereby their overall performance.

In industry, the recognition of the need to integrate these traditionally separated planning processes has led to the concept of integrated business planning (Ernst & Young, 2015a; KPMG, 2014; Pal Singh Toor and Dhir, 2011). However, academic research has not yet seized integrated business planning in a comprehensive and structured analysis. We contribute to the closing of this gap by analyzing integrated business planning for the case of the automotive industry. Our analysis focuses on both planning processes and decision support approaches (cf. Chapter 3).

This chapter provides a reference process for integrated business planning in the automotive industry, which systematically integrates long-term cyclic product planning with the planning of design projects, as well as the planning of design projects with the mid-term cyclic SOP process. It structures the relevant planning tasks and their interdependencies.

Based on the reference process, we develop a classification scheme to identify the resulting integration challenges faced by car manufacturers when coordinating project and cyclic planning. Based on the defined reference process and the identified integration challenges, we analyze the current industry practice to unveil shortcomings in integrated business planning at automotive OEMs.

To accomplish these goals, we followed a three-step approach. In a first step, we conducted a forward and backward search for academic literature on automotive planning processes using the ScienceDirect, Scopus, and Emerald Insight databases, as well as Google Scholar. Among others, we used the keywords "automotive industry", "capacity planning", "integrated business planning", "modularization", "platform design", "platform planning", "product design", "product development", "product planning", "production planning", "sales and operations planning", "strategic planning", "supply chain design", "supply chain planning", "tactical planning", and combinations thereof. A first filtering was performed based on titles and abstracts, before the text was analyzed to full extent. In addition to journal articles we screened Ph.D. dissertations

of the automotive research community in the US and Germany and included selected conference papers with a strong contribution to our topic. We limited the search period to the years 2000 and later and included literature cited in the publications detected.

We found a total of 44 publications with information on planning processes at more than ten different car manufacturers, covering several regions (North America, Europe, Japan, and Korea) and segments (premium and volume). Section 2.2 gives an overview of this literature, which includes literature reviews, planning frameworks, case studies, and modeling approaches.

In a second step, we performed interviews at three large passenger car manufacturers and two truck manufacturers that both are part of an automotive holding company and therefore have the same standardized planning processes established. At each manufacturer we conducted between two to seven interviews. We interviewed planners on the third to fourth management level responsible for supply chain management, production planning, sourcing, product planning, and the coordination of production ramp-up with product development. We used the concept of semi-structured interviews based on a first draft of the reference process, which was synthesized from the academic literature found in the first step, and focused on verifying the reference process and filling the blank spots. In particular, we extracted additional information about platform and module planning, the network design and capacity planning process for new products, and the ramp-up planning process at automotive manufacturers. Furthermore, important information on time windows, planning horizons, and planning frequencies could be obtained.

In the third step, we synthesized the primary data from the interviews and the secondary data from the literature review to define the reference process for car manufacturers and to identify the integration challenges. The reference process is therefore based on information on the planning processes of a total of at least 13 manufacturers (cf. Table 2.1, not all authors specify the exact OEM). Five manufacturers are covered by both interviews and academic literature; at least seven additional manufacturers can be found in academic publications. Thus, the defined reference process synthesizes information about the planning processes of manufacturers from all relevant regions, including France, Germany, Japan, South Korea, Sweden, and the US. Section 2.3 presents the reference process and Section 2.4 a classification scheme for the integration challenges. This section also outlines industry shortcomings in relation to the integration challenges.

2.2. Automotive planning processes in the academic literature

In this section we review the academic literature on planning processes in the automotive industry. The review is structured as follows. First, it outlines the literature on processes for the planning of design projects. Second, it discusses the literature on processes for cyclic planning. Third, it shows the research gap related to the reference process for integrated business planning at automotive OEMs.

2.2.1. Literature focusing on processes for product, process, and network design projects

The product development process in general has been extensively covered in academic literature. Several authors propose reference processes. Ulrich and Eppinger (2008) propose a six-stage process identifying the key tasks for involved planning functions. Cooper (2011) proposes a five-stage development process for complex products or technology platform projects using "stage gates" for coordination. Hab and Wagner (2013) describe a similar process used in the German automotive industry. Clark and Fujimoto (1991) give a reference process for product development in the automotive industry, including the process design and ramp-up and compare several OEMs from different regions. Muffatto and Roveda (2000) describe a reference process for product development based on platforms and discuss a case study of an OEM. Aoki and Stäblein (2017) analyze the interface of product design and manufacturing of Japanese and German automakers and identify capabilities required to manage dynamic product variety. Schuh et al. (2005) focus on the production ramp-up in the automotive industry and introduce four ramp-up strategies. Gopal et al. (2013) analyze the impact of new product introduction at North-American automotive production plants.

The decision-making process for strategic network design and capacity planning in the automotive industry has been discussed frequently, a field reviewed by Volling et al. (2013). For example Fleischmann et al. (2006) analyze the strategic planning process of BMW's global production network and Gneiting (2009) focuses on a strategic production design process based on a modular product architecture. Schmaußer (2011) describes the network design and capacity planning process at Audi and highlights the link of network design projects to product design projects. Recently, researchers have been focusing on the process for ramp-up planning at car manufacturers, e.g. in Becker et al. (2017) and

Wochner et al. (2016). Boysen et al. (2009) provide a design framework for the layout of mixed-model assembly lines in the automotive industry and provide a review of OR approaches. Moreover, the joint decision-making process for product and supply chain design has been gaining in importance (cf. the review Gan and Grunow, 2016).

The development of new process technologies has lately received coverage in the literature on planning processes. Bornschlegl et al. (2015) describe the interdependencies between the process for process technology design and the process for product development at OEMs. Peters (2015) investigates how these interdependencies influence the timing of investments in new process technologies.

2.2.2. Literature focusing on processes for cyclic planning

In the automotive industry, the product strategy is derived and regularly reviewed in a cyclic product planning process, in which platform and module strategies have become important topics over the last years. For example, de Weck (2006) analyzes the multi-platform planning process at car manufacturers. Lampón et al. (2015) describe the impact of modular platform strategies on planning processes for European and American OEMs. Robertson and Ulrich (1998) discuss the challenge of balancing commonality and distinctiveness in the platform planning process using an example of the automotive industry. Cornet (2002) outlines the decoupled development process for common modules in the automotive industry. Mikkola (2003) studies the planning process for a module strategy and the impact on the new product development process with focus on component outsourcing based on an automotive case study.

Both processes, platform planning and module planning, belong to the field of product variety management and target to implement mass customization. Processes for product variety management and their impact on other planning processes are reviewed in ElMaraghy et al. (2013). Various effects of the resulting commonality in an automotive context have been studied in academic literature. Moreno and Terwiesch (2017) find quantitative proof of a platform strategy's benefit to mitigate the cost increase due to product variety in the US automotive industry. Boas et al. (2013) find that commonality benefits are hard to realize for automotive manufacturers due to lifecycle offsets within product families. Verhoef et al. (2012) find that the loss of distinctiveness due to automotive platforms depends on the price segment. Ramdas and Randall (2008) show that commonality in the automotive industry has positive and negative impact on product quality. Pasche and Sköld (2012) discuss several drawbacks of common platforms and modules based on an automotive case study.

Also performed as cyclic process, however, at a lower planning level, S&OP has recently received a lot of attention in practice and academia, synthesized by Tavares Thomé et al. (2012) and Tuomikangas and Kaipia (2014). For example, Grimson and Pyke (2007) propose a general S&OP framework and Oliva and Watson (2011) discuss a detailed case study of an S&OP process. Linking the selection of a manufacturing strategy with S&OP in a general study, Olhager et al. (2001) identify important interactions in both directions and propose a framework supporting the joint selection of the capacity strategy and planning strategy for different production types.

In an automotive context, the mid-term S&OP process is often described jointly with the operational order fulfillment process, a field reviewed in Bartnik et al. (2016). Meyr (2004) analyzes tactical and operative supply chain planning processes in the German automotive industry and suggests a reference process combining tactical forecast-driven planning and operative order-driven scheduling. Comparing planning and scheduling processes of Japanese and German OEMs, Stäblein and Aoki (2015) identify similar processes in both countries. Tomino et al. (2009) discuss a process called "Market Flexible Customizing Systems" implemented by Japanese OEMs to support the integration of customer-specific orders into the forecast-driven production planning process. Hahn et al. (2000) describe the S&OP process at Hyundai, controlled by a central planning department and enabling alignment by frequent cross-functional meetings. Holweg (2003) synthesizes the order fulfillment process of two European, two American, and two Japanese car manufacturers and concludes that current processes are misaligned to external customer needs. Furthermore, Holweg and Pil (2004) identify only a very limited number of information systems used to support the automotive S&OP process in practice.

Some authors use simulation to analyze the S&OP process at car manufacturers. Volling and Spengler (2011) simulate the interdependency between "batch-processed" master production scheduling and "real-time-processed" order promising at car manufacturers. Lim et al. (2014b) simulate the S&OP process with focus on order booking, using a frozen horizon for long-distance supply in a tailored application with Renault. Holweg et al. (2005) simulate the order fulfillment process at OEMs and conclude that it is currently incapable of implementing a built to order (BTO) concept due to legacy IT-systems.

2.2.3. Process for integrated business planning

Table 2.1 summarizes the existing academic literature on automotive planning processes discussed in Sections 2.2.1 and 2.2.2. For each of the 44 publications, it clearly indicates the planning process(es) focused and, if any, the integration challenge(s) addressed. Furthermore, it shows the variety of OEMs used as basis for the existing academic research of automotive planning processes. It can be observed that academic literature has focused on particular areas of either project or cyclic planning. In total, only 16 publications address the integration of processes for the planning of projects and for cyclic planning at OEMs. Furthermore, these publications focus only on selected integration challenges. In most cases the addressed integration challenge is not studied in depth, but rather outlined on a higher level. Integration challenges on a tactical level, i.e. integrating supplier selection with supply planning and tactical ramp-up planning with S&OP (later referred to as Challenges 5 and 6), have not been discussed at all. Furthermore, most of the publications focus only on one OEM or on a specific region. Only a few publications make comparisons between different OEMs or regions.

Furthermore, the automotive planning processes described in the existing academic literature are in many cases characterized based on OEM-specific or region-specific perspectives. Thus, they lack an industry-wide synthesis and cannot be used as generic reference process. There is no reference process that integrates the project and the cyclic planning landscapes at OEMs in a comprehensive way and systematically identifies the integration challenges for integrated business planning in the automotive industry.

2.3. Reference process for integrated business planning in the automotive industry

2.3.1. Overview

The proposed reference planning process is organized by planning landscape, i.e., planning of design projects and cyclic planning, in the vertical dimension and time to production in the horizontal dimension, depending on the context, running toward the SOP for new vehicle types or day of production (DOP) for existing vehicle types (cf. Figure 2.2). In accordance with Fettke and Loos (2003), we define a reference process as an industry-specific, but, within this domain, generic description of the business processes. It enables the exchange of knowledge and indicates best practices.

Author (Year)	Processes for design projects			Cyclic planning processes				Integration challenge	Automotive OEM (brand, region)[1]
	(a) Process technology design	(b) New vehicle design	(c) Strategic network design	(d) Product planning	(e) Demand planning	(f) Sales & operations planning	(g) Order fulfillment		
Aoki and Stäblein (2017)	☑	☑	☑	☑	☐	☐	☐	1, 2	BMW, D, GM HO, MAZ, MIT, RN, T, VW
Becker et al. (2017)	☐	☐	☑	☐	☐	☐	☐	-	SA
Moreno and Terwiesch (2017)	☐	☐	☐	☑	☐	☐	☐	-	C, F, GM, HO, HY, RN, T
Bartnik et al. (2016)	☐	☐	☐	☐	☐	☑	☑	-	MA
Gan and Grunow, 2016	☐	☑	☑	☐	☐	☑	☐	4	-
Wochner et al. (2016)	☐	☐	☑	☐	☐	☐	☐	-	EU
Bornschlegl et al. (2015)	☑	☑	☐	☐	☐	☐	☐	-	SA
Lampón et al. (2015)	☐	☐	☑	☑	☐	☐	☐	1	BMW, D, GM, PSA, RN, VO, VW
Peters (2015)	☑	☐	☐	☐	☐	☐	☐	-	SA
Stäblein and Aoki (2015)	☐	☐	☐	☐	☑	☑	☑	-	GER, JAP
Lim et al. (2014a)	☐	☐	☐	☐	☐	☑	☐	-	RN
Tuomikangas and Kaipia (2014)	☐	☐	☐	☐	☐	☑	☐	-	-
Boas et al. (2013)	☐	☐	☐	☑	☐	☐	☐	-	SA
ElMaraghy et al. (2013)	☐	☑	☑	☑	☐	☐	☐	1	VW
Gopal et al. (2013)	☐	☑	☑	☐	☐	☑	☐	4	NA
Hab and Wagner (2013)	☐	☑	☑	☐	☐	☐	☐	-	GER
Volling et al. (2013)	☐	☐	☑	☐	☑	☑	☐	3, 4	MA
Tavares Thomé et al. (2012)	☐	☐	☐	☐	☐	☑	☐	-	-
Verhoef et al. (2012)	☐	☐	☐	☑	☐	☐	☐	-	T, VW
Cooper (2011)	☐	☑	☑	☐	☐	☐	☐	-	-
Oliva and Watson (2011)	☐	☐	☐	☐	☐	☑	☐	-	-
Pasche et al. (2011)	☐	☐	☐	☑	☐	☐	☐	-	SA
Schmausser (2011)	☐	☑	☑	☐	☐	☐	☐	-	VW
Volling and Spengler (2011)	☐	☐	☐	☐	☑	☑	☑	-	SA
Boysen et al. (2009)	☐	☐	☑	☐	☐	☑	☑	4	VW
Gneiting (2009)	☐	☐	☑	☑	☐	☐	☐	1	D
Tomino et al. (2009)	☐	☐	☐	☐	☐	☑	☑	-	MAZ, RN, T
Ramdas and Randall (2008)	☐	☐	☐	☑	☐	☐	☐	-	F
Ulrich and Eppinger (2008)	☐	☑	☑	☑	☐	☐	☐	1, 3	-
Grimson and Pyke (2007)	☐	☐	☐	☐	☐	☑	☐	-	-
De Weck (2006)	☐	☑	☑	☑	☐	☐	☐	1	NA
Fleischmann et al. (2006)	☐	☑	☑	☐	☑	☐	☐	3	BMW
Holweg et al. (2005)	☐	☐	☐	☐	☐	☑	☑	-	EU, JAP, NA
Schuh et al. (2005)	☐	☐	☑	☐	☐	☐	☐	-	-
Meyr (2004)	☐	☐	☐	☐	☐	☑	☑	-	GER
Holweg and Pil (2004)	☐	☐	☐	☐	☑	☑	☑	-	EU, JAP, NA
Holweg (2003)	☐	☐	☐	☐	☐	☑	☑	-	EU, JAP, NA
Mikkola (2003)	☐	☑	☑	☑	☐	☐	☐	1, 2	C
Cornet (2002)	☐	☑	☑	☑	☐	☐	☐	1	MA
Olhager et al. (2001)	☐	☐	☑	☐	☐	☑	☐	4	-
Hahn et al. (2000)	☐	☐	☐	☐	☐	☑	☑	-	HY
Muffatto and Roveda (2000)	☐	☑	☐	☑	☐	☐	☐	1	SA
Robertson and Ulrich (1998)	☐	☑	☐	☑	☐	☐	☐	-	SA
Clark and Fujimoto (1991)	☑	☑	☑	☑	☑	☐	☐	1, 3	MA

1 BMW – Bayerische Motoren Werke, C – Chrysler, D – Daimler, EU – European manufacturer(s), F – Ford, GER– German manufacturer(s), GM – General Motors, HO – Honda, HY – Hyundai, JAP – Japanese manufacturer(s), MA – multiple automotive manufacturer, MAZ – Mazda, MIT – Mitsubishi, NA – North American manufacturer(s), PSA – Peugeot Citroën, RN – Renault Nissan, T – SA – single automotive manufacturer, T – Toyota, VO – Volvo, VW – Volkswagen.

Table 2.1: Overview of publications describing automotive planning processes.
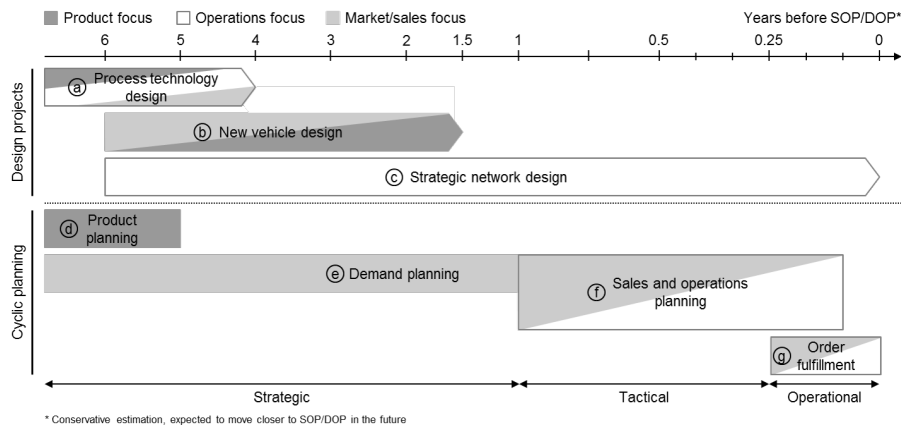
Figure 2.2: Overview of reference process for integrated business planning at automotive OEMs.

Based on the information extracted from our interviews, there are three processes for design projects: (a) New manufacturing technologies are introduced in separate long-term *process technology design* projects; (b) every new vehicle type is designed and tested in a separate *new vehicle design* project, while (c) the associated production and sourcing networks are developed in a parallel *strategic network design* project. In the following, *strategic network design* is further distinguished into *production network design* and *sourcing network design*. Furthermore, cyclic planning consists of four processes: (d) The overall product portfolio is defined in *product planning*, (e) volume forecasts are derived in *demand planning*, and the tactical and operational planning for the existing vehicle types is managed in (f) *S&OP* and (g) *order fulfillment*.

The detailed reference process is shown in Figure 2.3 and descried in detail in the following. It synthesizes information about planning processes of in total 13 OEMs, covering all relevant regions, based on the academic literature and on the interviews conducted. Time estimations are conservative and expected to move closer toward SOP and DOP in the future. If we found proof that process tasks or timing vary significantly between manufacturers, e.g. depending on the region or segment, we clearly highlight the variation. Information exchange between design projects and cyclic processes is depicted as arcs: Instructions are indicated by black arcs, feedback by white arcs, applying the concept of hierarchical planning (Schneeweiss, 1998). The following discussion starts with the strategic cyclic processes, i.e. (d) *product planning* and (e) *demand planning*, followed by the processes for the three types of design projects (a - c), and is completed by the tactical (f) *S&OP* process. As other papers have extensively covered (g) *order fulfillment*, it is only outlined briefly.

2.3.2. Cyclic product planning process

Having moved toward vehicle platforms and a modular product architecture, OEMs usually separate *product planning* into *platform planning*, i.e. taking the product perspective, and *module planning*, i.e. taking the module perspective (Cornet, 2002). In *platform planning*, the future product portfolio, which is based on a multi-platform strategy (de Weck, 2006), is defined and reviewed every year with a planning horizon of more than ten years. The vehicle platform is defined as a collection of assets, e.g. components, technologies or processes, shared by several vehicle types (Robertson and Ulrich, 1998), resulting in cheaper, more flexible, and more responsive design, planning, and manufacturing processes (ElMaraghy et al., 2013). It typically consists of drivetrain components (e.g. front and rear axles, steering system, braking system), the underbody-structure
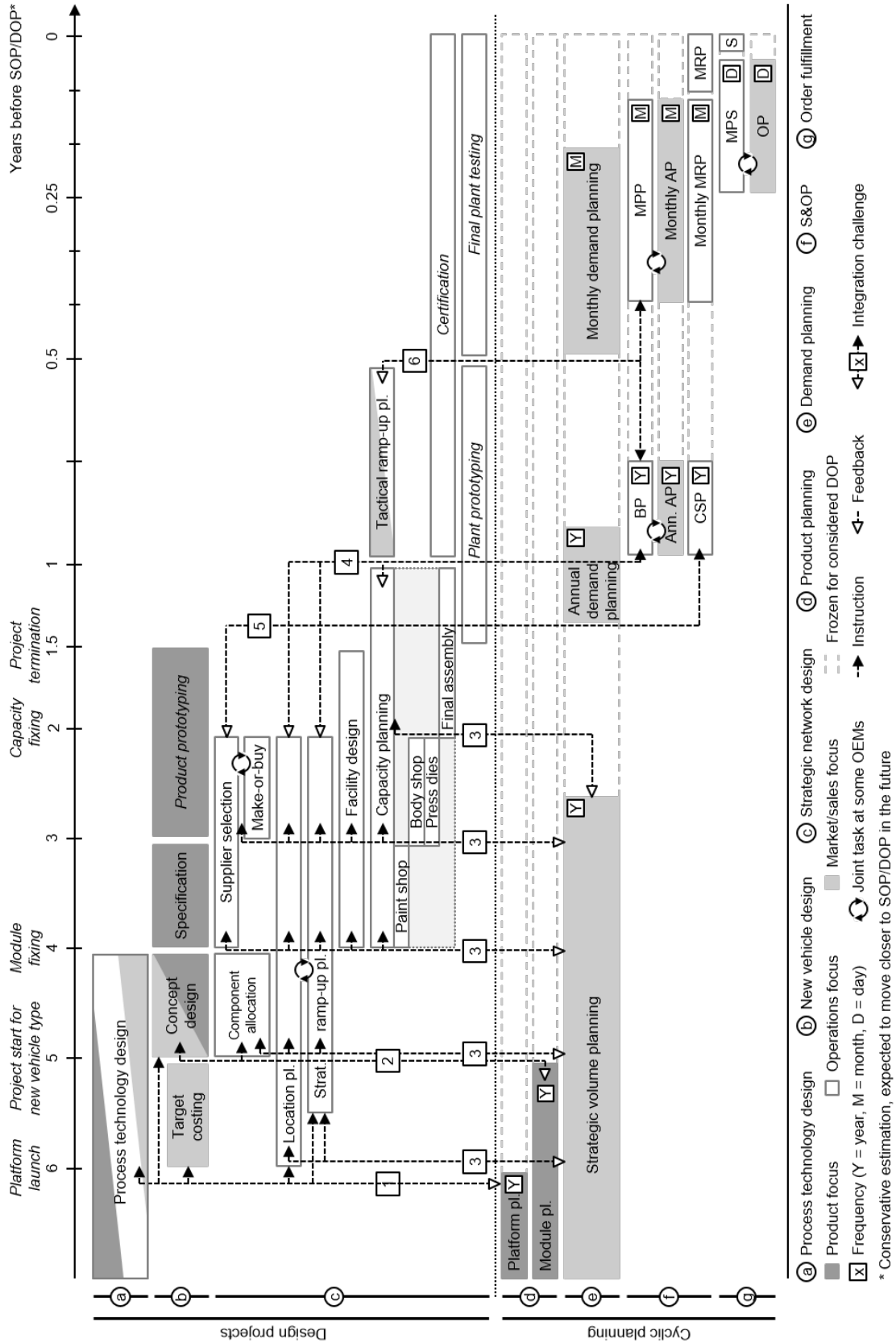
Figure 2.3: Detailed reference process for integrated business planning at automotive OEMs.
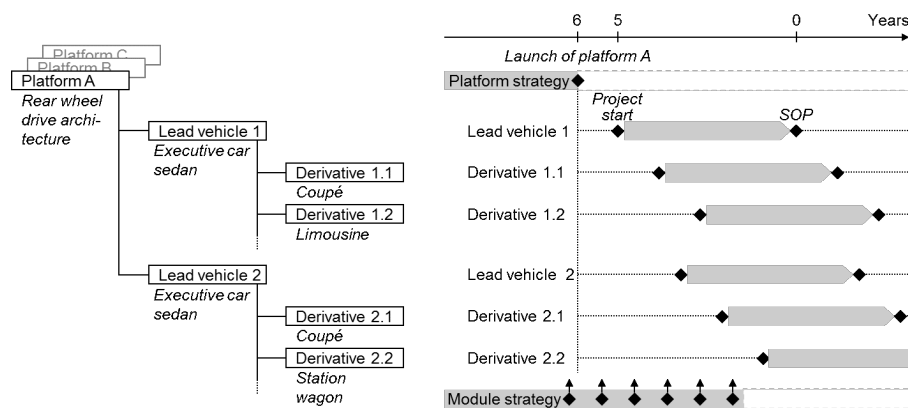
Figure 2.4: Example for a vehicle platform portfolio (left) and the resulting project plan (right).

(e.g. center floor, fuel tanks, and exhaust systems), seat frames, and electrical parts or subsets thereof. Multiple platforms are necessary to cover the broad range of customer preferences in the automotive market and implement various vehicle architectures, e.g. with front-wheel drive and rear-wheel drive.

Figure 2.4 shows an example of a platform strategy based on information extracted from our interviews. Each platform is used by one or more lead vehicle types (e.g. sedan) and their derivatives (e.g. station wagon or coupé). In the following, we will refer to both lead vehicle type and derivative as "vehicle types". Vehicles of one platform, however, can target different segments, resulting in a significant risk of loss of diversification and cannibalization (Boas et al., 2013; Verhoef et al., 2012).

The platform strategy consists of three major decisions, the total number of platforms maintained, the allocation of vehicle types to platforms (platform portfolio), and the platform selection, i.e. the common platform parts and dimensions (de Weck, 2006). The strategy is fixed for a specific platform with the "platform launch" six years before the SOP of the first lead vehicle type (based on interviews).

In *module planning*, the current module strategy is derived and reviewed. It defines the generic module structure across all vehicle types, the type of each module, and the module lifecycle. A module can be of common, similar, or independent type (Fujita, 2002). For a similar module, the module strategy also defines its variants and extent, i.e. for which vehicle types the module variant is used.

Every module lifecycle is detached from the vehicle type or platform lifecycles. As illustrated in Figure 2.4, the module strategy is reviewed regularly by a dedicated committee in cycles of six months to one year and serves as input for the projects for *new*

vehicle design and *strategic network design* (based on interviews).

Modern vehicle platforms combine a modular architecture with a scalable approach (Aoki and Stäblein, 2017; Lampón et al., 2015). Scalable dimensions, e.g. the wheelbase, make a platform deployable in several vehicle segments. The modular architecture facilitates the use of several module variants with the same platform and increases the potential for differentiation. Hence, platform and module strategies are related to each other. However, as they differ in scope, lifecycles, and key decisions, they are managed separately.

2.3.3. Strategic volume planning process

Strategic volume planning annually determines the central, long-term demand forecast used in the design projects. During our interviews, we detected a cross-functional process involving sales, as well as R&D, taking up to several months every year. The central demand forecast uses a planning horizon of more than ten years and is finalized six months before the following year. *Demand planning* on the tactical level is discussed as part of *S&OP* in Section 2.3.5.

2.3.4. Process for the planning of design projects

Target costing defines the financial boundaries for the vehicle types of the launched platform before the project start of the first vehicle type, roughly five years before its SOP (based on interviews). Estimated target costs for the vehicle type and its components are derived from a target profit used as input for downstream decisions. Similarly, target values are derived for capacity investments.

At the same time, potential production sites for the platform and its vehicle types are proposed in *location planning* and *strategic ramp-up planning*. In *location planning*, the production network structure, i.e. the allocation of production stages to plants, and the platform-to-plant allocation are decided. This can include the selection of new locations, e.g. for a full plant or a completely knocked down (CKD) assembly in a developing country (Fleischmann et al., 2006). In *strategic ramp-up planning*, this is further broken down for the vehicle types of the platform. The platform lifecycle plan is defined; this contains the sequence and timing of the production cycles for all vehicle types of the platform (Becker et al., 2017). Furthermore, the vehicle-type-to-plant allocation is decided, i.e. the selection of plants for each vehicle type. Roughly four years before SOP, a proposal for the allocation is made in order to enable *facility design* and *capacity*

planning. The final allocation decisions are made in the distinct vehicle type projects, not later than two years before SOP (based on interviews).

During our interviews we learned that in parallel, premature process technologies are developed in *process technology design*, which defines the boundaries for the future manufacturing costs. Recent examples are the manufacturing technologies developed for alternative powertrains or lightweight body design (Peters, 2015). If a new process technology is needed for a specific vehicle type, the technology design project has to be finished before *capacity planning* begins, i.e. not later than four years before the SOP (Bornschlegl et al., 2015).

Based on information extracted from our interviews, the dedicated *new vehicle design project* for a specific vehicle type of a platform starts at some OEMs already five years before its planned SOP. The duration of the projects varies across segments and regions. It is longest for premium manufacturers and is considerably shorter for Japanese OEMs (Aoki and Stäblein, 2017). Furthermore, non-lead-vehicle types have shorter development times than lead vehicle types. In *concept design*, the vehicle concept is developed by R&D and described in the concept booklet. The concept is a description of technology, working principles, form, and size of a product (Ulrich and Eppinger, 2008). The concept booklet defines the boundaries for the upcoming *make-or-buy* decision and *supplier selection* by categorizing parts into "make", "buy", or "make/buy" and defining multiple vs. single sourcing requirements (based on interviews). Once the concept booklet is finished, it initiates the *specification* phase, during which the vehicle type and its single components are technically described in detail. It is followed by the prototyping. The development of the vehicle type is terminated 1.5 years before SOP.

Along with the start of the project for a vehicle type, the associated *strategic network design* project is initiated (Clark and Fujimoto, 1991; Hab and Wagner, 2013). During our interviews we found that a *component allocation* roadmap for the parts of the new vehicle type is generated by the buyers responsible. Modules and components categorized as "buy" or "make/buy" are allocated to a set of suppliers based on expected lifecycle volumes, target costs, and the preliminary vehicle concept. The results are fixed four years before the SOP. The preliminary allocation of parts to suppliers is based on a letter of intent, which has no contractual obligation, but which forms the basis for further planning decisions for both sides, supplier and OEM.

Once a part is fully specified, the *supplier selection* process can be initiated for all "buy" and "make/buy" parts (Mikkola, 2003). It starts with more complex components having the longest development time, e.g. electronic components, the cockpit or

bumpers. Prices are negotiated based on the target costs and the long-term demand forecast derived by *strategic volume planning*. The evaluation and selection of suppliers must be terminated two to three years before the SOP, varying across the components (based on interviews). Furthermore, all parts are finally assigned as being "make" or "buy" only. Some OEMs already finalize contracts with the selected suppliers at this stage, specifying the volumes for the entire lifecycle or for the time until the "facelift" (mid-life model update) is launched, others draw up annual contracts later as part of annual *component supply planning (CSP)* in *S&OP*.

Facility design is done for both existing and new sites, based on the preliminary location selection and, once available, the final network decisions from *location planning*. Its major concern is the plant layout, i.e. the physical arrangement of the production stages, logistics hubs, warehouses, etc. During our interviews we found that preliminary construction work is started three years before SOP, even though, at this point in time the production network decisions are not yet final.

In parallel, *capacity planning* is conducted at the sites selected for the new vehicle type. The typical automotive manufacturing process consists of press shop, body shop, paint shop, and final assembly (Volling et al., 2013). Thus, for each stage, decisions must be made on the annual technical capacity level, i.e. units per year, and the detailed process layout, i.e. number of lines, balancing of the lines, number and type of machines, level of automation, etc. (Boysen et al., 2009; Schmaußer, 2011). The inputs are the long-term demand forecast, the vehicle concept and specification booklets, the new *process technology design* (if applicable), and assumptions on tactical parameters for *S&OP*, i.e. production rates and shift models (based on interviews). Furthermore, equipment suppliers are selected and the capacity investment is decided.

Each production stage has significantly different characteristics that impact *capacity planning*. We learned during our interviews that the different characteristics result in severe planning time lags and therefore in sequential decision making for a new vehicle type, as discussed in the following.

In the press shop, the skin parts are forged. Due to the expensive machinery, not every plant operates its own press shop. It can be shared by several vehicle types, even across platforms. The press dies, however, are specific to vehicle types. The necessary changing of dies between production runs results in long setup times (Wittek, 2013). In the body shop, the body in white is assembled, a vehicle type-specific operation with very limited flexibility potential (Friese, 2008). Thus, OEMs usually maintain a dedicated line for each vehicle type (Fleischmann et al., 2006). However, recent innovations in

process technology and product design allow expensive body shop layouts with increased flexibility within one platform (Lampón et al., 2015). The body shop processes need to operate with a very high level of precision (Sillekens, 2008). Thus, the automation level is typically very high, which calls for high investments and long lead times (Holweg and Pil, 2004). Combined the two stages account for roughly 60 percent of the total investments. *Capacity planning* is started early and finished two years before SOP for the body shop and the press dies.

The paint shop uses automated, though more flexible processes (Friese, 2008) and is thus also investment-intense. As the supplier market for the specific equipment is very small, the development and construction time is even longer than for the body and press shop. Due to the high process flexibility, all vehicle types or platforms can share the same paint shop line (Fleischmann et al., 2006). If a new paint shop is needed, *capacity planning* must already be finished three years before SOP.

In the final assembly stage, the painted body and the powertrain are joined and the interior, exterior, and electronics components are assembled. Due to the high diversification level, manual processes are mostly used. Thus, the development and construction time is shorter and the timing of *capacity planning* is less restricted with a final decision one year before the SOP. Lines can be operated as mixed-model or solitary assembly lines (Holweg and Pil, 2004). In addition, multiple parallel lines are possible.

Once *capacity planning* is finished, the construction of a prototype plant and the plant certification process begin (based on interviews). The production tests in the prototype plant are finished six months before the SOP and performed with generic equipment with exception of the body and press shop, where vehicle type-specific tools are already used. Finally, up to six months before SOP, the final plant construction is finished and production tests are started on site.

In parallel, six to 12 months before the SOP, *tactical ramp-up planning* determines the detailed production ramp-up curve for the new vehicle type. The market launch scheme is also derived, which specifies the timing of the region-specific market introduction and coordinates the distribution of volumes to specific sales regions during the ramp-up phase (Wochner et al., 2016).

2.3.5. Sales and operations planning process

S&OP in the automotive industry consists of two forecast-driven planning cycles using an annual and a monthly frequency, respectively. The annual cycle consists of *budget planning (BP)* combined with annual *allocation planning (AP)*, *CSP*, and *demand plan-*

ning. At Japanese OEMs, the planning frequency is increased to six months, however, the role and importance of the tasks are comparable (Tomino et al., 2009).

Other terms can be found for *BP*, e.g. "anticipatory schedule". It is the central *S&OP* task in the annual cycle, involving representatives from the central sales, production, and procurement departments (Meyr, 2004). Overall, the monetary budget and the central annual production plan are derived with a monthly granularity covering all plants and vehicle types. *BP* depends on mid-term forecasts derived during the annual *demand planning.* The central production plan is used as production volume goal for the monthly cycle.

Moreover, it is transformed into a central annual sales plan containing aggregate quotas, which again are volume goals for the monthly cycle and are further distributed within the sales organization in annual *AP.* In addition, *BP* determines a high level annual workforce plan, e.g. specifying the annual working time model, hiring and layoffs.

In a flexible production network, *BP* is also concerned with mid-term reallocation of vehicle types to lines or plants (Wittek, 2013) or a potential reconfiguration of assembly lines (Boysen et al., 2009).

The annual *CSP* is based on the results of *BP* and the expected option take rates forecasted by *demand planning.* As mentioned in Section 2.3.4, varying across OEMs, it can be responsible for the annual volume-binding supply contracting that occurs ten months before the associated planning year.

In the monthly cycle, *master production planning (MPP)* is the central *S&OP* task. It is the lowest planning level concerned with matching supply and demand across the entire network. The planning horizon is between three months to one year (Meyr, 2004). Depending on the level of specification, the frozen horizon varies from three months (body type) to one month (options).

MPP determines central monthly production plans and sales plans (quotas) with more detailed product features and weekly granularity to meet the annual volume goals defined in *BP* (Meyr, 2004). Furthermore, the workforce schedule for the month(s) to come is refined, e.g. by specifying shift models and use of overtime or temporary workers. Many OEM have established monthly cross-functional *S&OP* meetings at senior management level with board participation (Hahn et al., 2000).

The demand forecasts used for *MPP* are updated more frequently than the forecasts used for *BP* and are more accurate due to the shorter time to production, which reduces uncertainty due to a higher ratio of already specified orders (Meyr, 2004).

Based on the results of the *MPP*, monthly *material requirements planning (MRP)*

defines the component supply for the next months within the boundaries of the supply contracts described earlier. The planning frequency is one month, the planning horizon varies between as little as three and as many as 12 months (Stäblein and Aoki, 2015). Plans are usually frozen one month before DOP. However, this can happen earlier for components with a long lead time (Lim et al., 2014b). The longer the planning horizon and the earlier the supply plans are frozen, the more inaccurate is the information on the demanded options, which explains the increased use of take rates in such cases.

2.3.6. Order fulfillment process

Finally, the *order fulfillment* process comprises order-driven scheduling on a weekly to daily basis. In general, planning is narrowed down from a company-wide approach to the single entities, i.e. sites, lines, etc. In *master production scheduling (MPS)*, real orders are integrated into the production plans delivered from *MPP* by a central order management department. At some OEM, this is also called "slotting" (based on interviews).

Orders are assigned to a production site and are integrated into the site's master production schedule via *order promising (OP)* in a central online order bank (Volling and Spengler, 2011). Its detailed short-term schedules consider model-mix constraints and perform the line assignment in daily buckets. They are frozen ten to 14 days before DOP and serve as input for short-term *MRP* and *sequencing (S)*, which finally determines the exact car sequence for each line (Holweg et al., 2005). The car sequence is frozen four to eight days before DOP. The resulting final assembly sequence is further used for the *sequencing* of upstream production stages, i.e. paint, body, and press shop, and the derivation of just in time (JIT)/just in sequence (JIS) signals. For further details we refer to (Bartnik et al., 2016).

2.4. Integration challenges and industry shortcomings

Cyclic planning processes have to provide the continuity required for the alignment of the various design projects. The resulting central role of the cyclic planning processes leads to the two types of integration illustrated in Figure 2.5. Multiple parallel design projects diverge from a cyclic process at the strategic level. Furthermore, design projects converge into a cyclic process at the tactical level. Thus, in our analysis we always focus on one cyclic process and the associated diverging or converging design projects, even
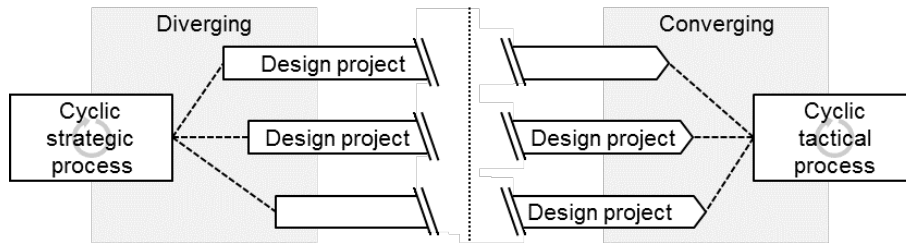
Figure 2.5: Two types of integration – diverging (left) and converging (right).

though several cyclic processes may exist in parallel.

We identify the six integration challenges shown in Figure 2.3, which arise from the need for coordination across the two separate planning landscapes and must be supported by the integrated business planning process of an OEM. According to the classification scheme in Figure 2.5, three integration challenges are based on divergence of design projects from a cyclic process, i.e. from *platform planning*, *module planning*, and *strategic volume planning*. Convergence is observed for the integration of the *strategic network design* projects with cyclic *S&OP*. In the following, the six integration challenges are discussed in more detail based on this hierarchy.

2.4.1. Diverging from a cyclic process into design projects

Challenge 1. *Diverging cyclic platform planning into design projects.*

The platform strategy derived in annual *platform planning* constitutes the basis for the planning tasks in every design project. For every future vehicle type, it defines the boundaries for the detailed vehicle concept, the network structure, the applicability of new process technologies, and the resulting target costs. Thus, as illustrated in Figure 2.6, design projects of all three types diverge from *platform planning*.

The design projects are characterized by a long duration combined with project launches spread out over several years. Thus, changes to a specific platform after the first associated *vehicle type design* or *network design* project is initiated can result in a major loss of synergy effects. To prevent this, an early platform freeze is used by many OEMs, termed "platform launch" (cf. Figure 2.3 and Figure 2.4). It fixes a platform and its portfolio of vehicle types about six years before the first SOP (based on interviews). However, such a freeze has an irreversible and long-term impact (more than ten years when the development time and the lifecycle duration of all vehicle types of the platform is taken into consideration), and substantially reduces the flexibility of the OEM at a very early stage in the product development process.
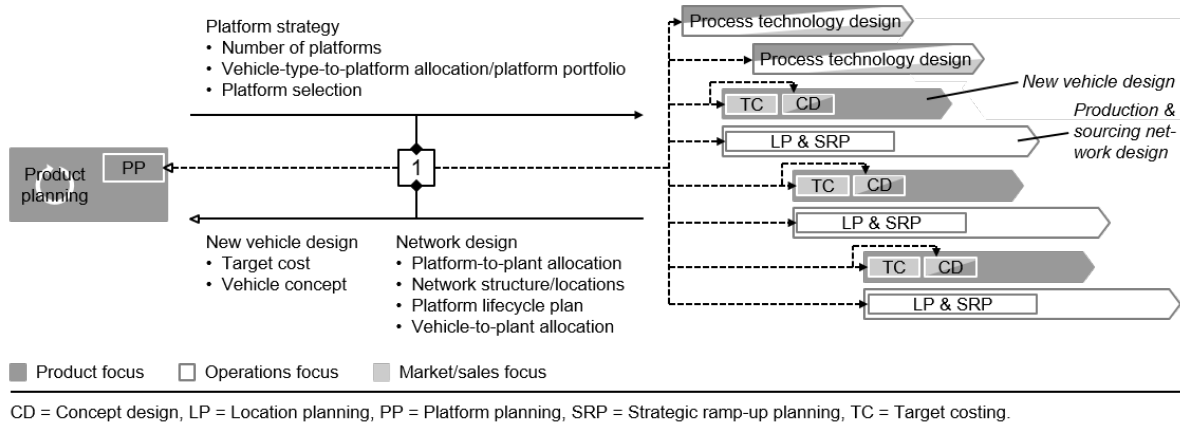
Figure 2.6: Overview of diverging cyclic platform planning into design projects.

Thus, before the freeze, the consequences of the platform alternatives for the associated design projects must be investigated. Implications for the detailed vehicle concept and the associated customer acceptance must be analyzed for each specific vehicle type (integration of *new vehicle design*), the required investments into flexibility and capacity of the production network must be evaluated and timing conflicts resolved (integration of *production network design*), and the timing of the *process technology design* projects, which are critical for the platform, must be aligned with the platform lifecycle. A lack of proper alignment before the freeze can lead to higher unit costs, unexpected investments, lost sales due to postponed product introductions, competitive disadvantage due to old-fashioned technologies, and customer rejection due to deviations from the core requirements.

Therefore, OEMs approach *platform planning* in cross-functional teams involving R&D, operations, and marketing to anticipate the implications for the associated design projects. Hence, alignment is established, focusing on the projects for *new vehicle type design* and *strategic network design*. However, influence and power of the different functions vary across OEMs. For example, at German OEMs the alignment is typically in favor of R&D, while at Japanese OEMs marketing has a stronger influence.

Furthermore, for *process technology design* projects, a one-sided dynamic can be observed in the current industry practice. However, the coordination is handled differently across the regions (based on interviews). At European OEMs, for example, the timing of *process technology design* projects is strongly driven by the "platform launch", i.e. the development of the process technology must be terminated in time to be used for a specific platform or vehicle type, i.e. by no later than the beginning of *capacity planning*. At Japanese OEMs, the timing is detached from the "platform launch", i.e. a platform
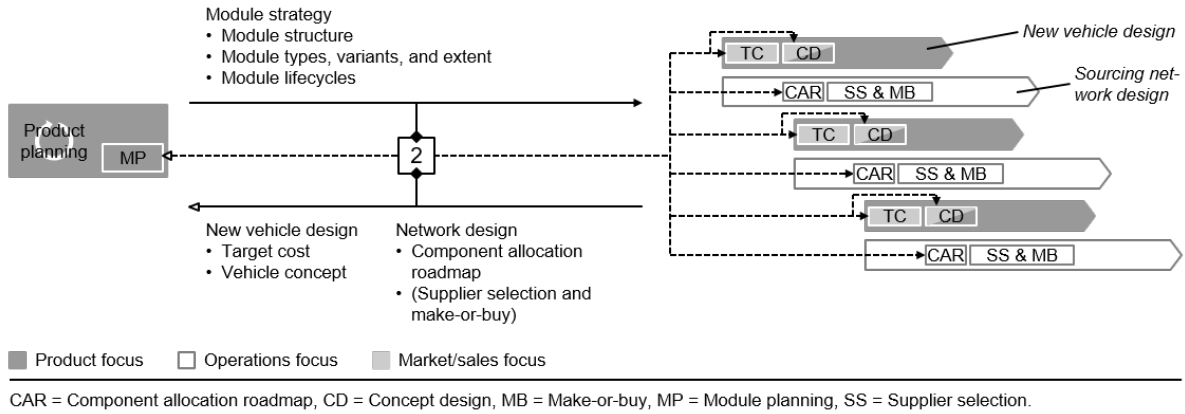
Figure 2.7: Overview of diverging cyclic module planning into new vehicle design and sourcing network design.

is launched independently of the development status of the process technology. The corresponding *vehicle type design* and *network design* projects simply choose from the technologies available at this point in time.

Based on our interviews, it can be concluded that the most OEMs have recognized the need for an integrated business planning process and established a basic coordination mechanism for the integration of *platform planning* with the diverging design projects, though at the cost of flexibility. In addition, OEMs should target a more balanced alignment and a higher degree of integration.

Challenge 2. *Diverging cyclic module planning into new vehicle design and sourcing network design.*

Similar to Challenge 1, *module planning* delivers the planning basis for the *new vehicle design* and *sourcing network design* projects, as shown in Figure 2.7. However, the scope can also include vehicle types of other platforms, depending on the extent and lifecycle of common modules.

In our interviews we detected that the module strategy is updated in (bi-) annual cycles. To guarantee a consistent planning basis for every multi-year project, many OEMs use a module strategy freeze with respect to the corresponding new vehicle type about four years before its SOP. This is termed "module fixing" (cf. Figure 2.3). Due to the early freeze, the OEM again loses the flexibility to react to unforeseen developments during the project.

Thus, before the freeze, the module strategy must be aligned across all *vehicle design* and *sourcing network design* projects, in order to trade off scale effects and the need
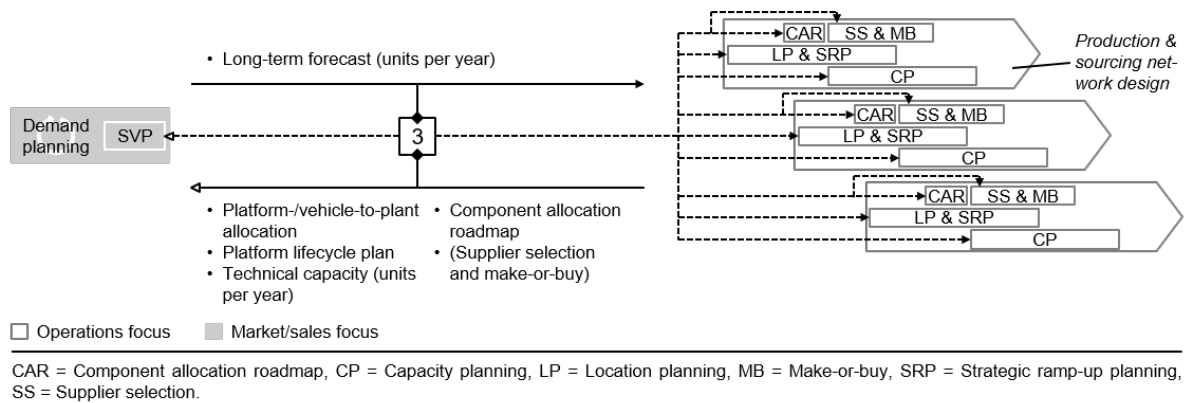
Figure 2.8: Overview of diverging cyclic strategic volume planning into strategic network design.

for innovation for the common modules. Furthermore, the compatibility of the module structure with the vehicle concept of the future vehicle types must be analyzed and the module lifecycles must be aligned with the lifecycle of each vehicle type. In addition, the *component allocation* roadmap for the relevant vehicle types must be anticipated during *module planning* to understand which module structure is most appropriate from the sourcing perspective, e.g. with respect to the available suppliers or the sourcing strategy and organization. Mismanagement will lead to either reduced scale effects of the module strategy due to unforeseen module adjustments during its lifecycle or lost sales due to postponed product innovations.

Thus, OEMs that follow a module strategy approach typically have dedicated cross-functional teams for each common module involving R&D, operations, and marketing to manage the module during its lifecycle. Furthermore, regular alignment meetings with vehicle type managers are established.

Challenge 3. *Diverging cyclic strategic volume planning into strategic network design.*

Strategic volume planning updates the long-term forecast in annual planning cycles and distributes it to all *strategic network design* projects to be used as planning volume, as shown in Figure 2.8. However, the various decisions in *strategic network design* are subject to planning time-lags causing sequential decision making (cf. Figure 2.3). Thus, due to the annual updating the decisions are based on different versions of the forecast leading to potential misalignment (based on interviews).

According to information extracted from our interviews, OEMs typically conduct a process termed "capacity fixing", in which they freeze the planning volumes for a *strategic network design* project roughly two years before the SOP of the associated vehicle type,

to prevent misaligned decisions and enable efficient construction and capacity ramp-up (cf. Figure 2.3). However, as the decision timing is artificially accelerated for some of the decisions, a freeze also reduces the flexibility required to react to uncertainties and reduce the investment risk.

A more advanced coordination as part of an integrated business planning process must facilitate the cross-functional alignment of *strategic volume planning* and *strategic network design*, e.g. by involving the operations function in *strategic volume planning* based on a balancing process similar to the *S&OP* process at the tactical level. Consequently, the decisions made earlier in the projects could be considered in order to understand the implication of the updated volumes with respect to extra invest, lost sales, or overcapacities. Likewise, planning could be aligned across all *strategic network design* projects.

2.4.2. Converging design projects into the cyclic sales and operations planning process

Challenge 4. *Converging location, strategic ramp-up, and capacity planning into cyclic budget planning.*

Figure 2.9 shows the convergence of the parallel *production network design* projects into *S&OP*. Here, the aggregate plans derived in *BP* must be anticipated during the *production network design* projects to consider effects of reallocations in the production network and estimate real capacities based on the expected workforce plans. Furthermore, scale effects during the lifecycle of the new vehicle type must be estimated, e.g. resulting from synergies with vehicle types of the same platform or complexities with vehicle types of different platforms produced on the same line. At the same time, a new platform lifecycle plan and changes to the network structure and to a site's capacity or layout alter the planning basis for *BP* and have an impact on the ongoing production of other vehicle types.

Consequently, both alignment across the diverse *production network design* projects and between the projects and *BP* is required. This is particularly challenging due to the increased number of parallel projects. Without an integrated business planning process enabling such an alignment, expensive network flexibility will stay unused, capacity utilization will be inefficient, and realized capacity levels will differ from the planned levels, causing expensive corrections during the lifecycle. Furthermore, delayed product launches and disturbances in the production of other vehicle types during a ramp-up
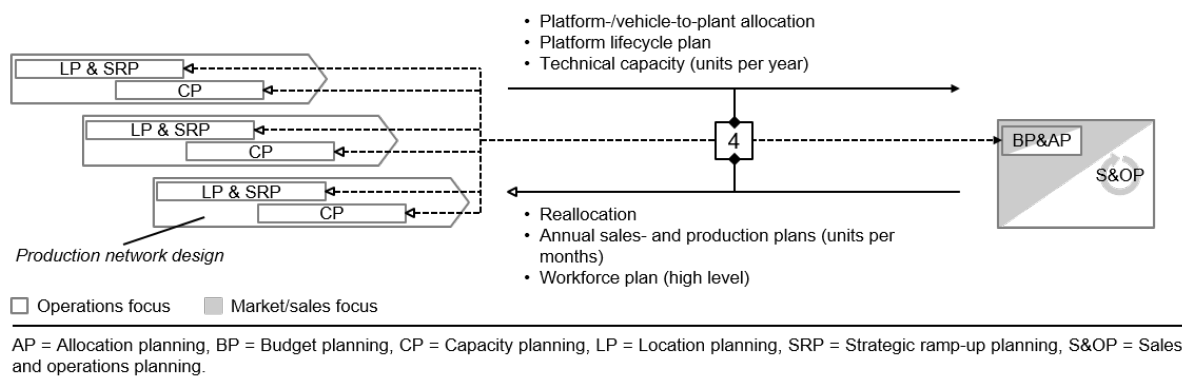
Figure 2.9: Overview of converging location, strategic ramp-up, and capacity planning into cyclic budget planning.

phase become more likely, implying the risk of lost sales due to delays in the order fulfillment.

Based on our analysis of the primary (interviews) and secondary data (literature), no structured process at OEMs to support the convergence of *production network design* projects into cyclic *S&OP* could be identified. Processes for *production network design* and *BP* are historically separated, leading to a lack of alignment and transparency. Similarly, the systems employed for *S&OP* do not link to the design projects. The delay in product launches due to unforeseen complexities on the shop floor is just one recent example from the automotive sector emphasizing this finding. It must therefore be assumed that synergy effects in production are currently not being achieved in full and that inefficiencies caused by the ramp-up situations are underestimated.

Challenge 5. *Converging supplier selection and make-or-buy into cyclic component supply planning.*

Similar to Challenge 4, the decisions on *supplier selection* and *make-or-buy* in the *sourcing network design* projects and the annual *CSP* for the existing vehicle types in *S&OP* must be aligned in order to understand reciprocal effects, as shown in Figure 2.10. Information on the extent of sharing and the total volume of a common module that is sourced from a specific supplier must be synthesized for all vehicle types, the new vehicle types, for which the sourcing network is designed, and the existing vehicle types.

Therefore, sourcing must be planned module-oriented, across vehicle types and platforms, to achieve appropriate volume discounts when negotiating supply contracts. Otherwise, the expected savings effects of the module strategy pursued will not materialize in full. This holds true, regardless of whether contracts are negotiated during the *sourcing*
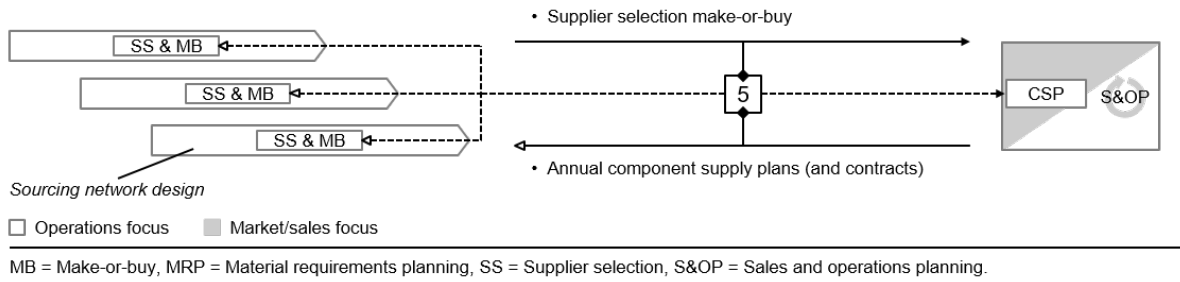
Figure 2.10: Overview of converging supplier selection and make-or-buy into cyclic component supply planning.
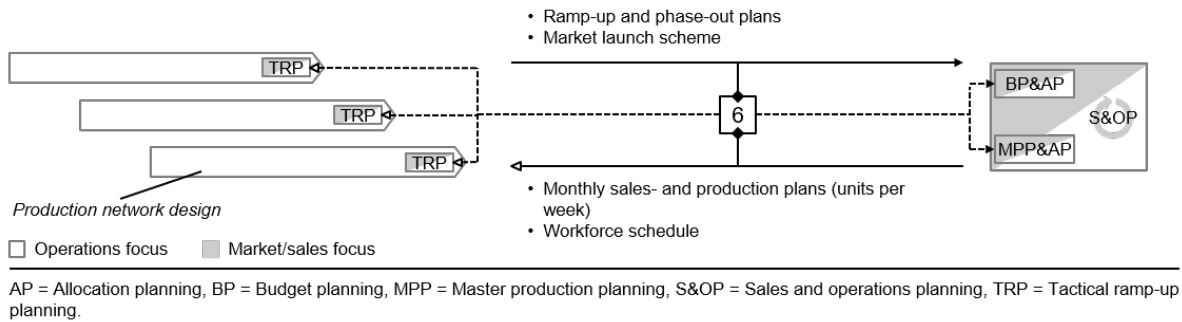
Figure 2.11: Overview of converging tactical ramp-up planning into cyclic S&OP.

network design or during the annual *CSP*.

It could be observed during our interviews that many OEMs negotiate contracts separately for individual vehicle types. This results directly from the organization of the procurement department that is still structured according to individual vehicle types, leading to a lack of transparency and alignment.

Challenge 6. *Converging tactical ramp-up planning into the cyclic S&OP process.*

Finally, the *production network design* projects are terminated and converge into *S&OP* at the tactical level, shown in Figure 2.11. Thus, the ramp-up and phase-out plans derived in *tactical ramp-up planning* must be integrated into the central plans of the *S&OP* derived in *BP* and *MPP*.

Therefore, the aggregate production plans in *S&OP* must incorporate the ramp-up schedules of all new vehicle types introduced over the associated planning horizon. Furthermore, the effects on the production of other vehicle types must be considered, e.g. reduced efficiency, reduced capacity or higher labor requirements due to training. Thus, shift plans and workforce training must be adapted to guarantee both smooth production of the existing vehicle types and efficient ramp-up. Also, the market launch scheme

of each new vehicle type must be considered in the sales quotas derived in *MPP*.

Due to the increasing number of ramp-ups, the convergence of the *tactical ramp-up* projects into *S&OP* has become a challenge and must be supported by an integrated business planning process. Otherwise, unforeseen disturbances and confusion on the shop floor will lead to prolonged ramp-up phases for the new vehicle types and delays in order fulfillment of the vehicle types produced on the same line. Similar to Challenges 4 and 5, no firmly established coordination mechanism to support the convergence of *tactical ramp-up* projects into *S&OP* could be identified in industrial practice, based on our interviews or the existing academic literature.

2.5. Conclusion

We have presented a reference process for integrated business planning. This reference process integrates the cyclic processes of *S&OP*, *demand planning*, and *product planning* with the planning processes of design projects, i.e. *new vehicle design*, *strategic network design*, and *process technology design*. Based on this reference process, we identified the resulting integration challenges for automotive OEMs and defined a classification scheme. Two types of integration challenges are distinguished: challenges connected to the divergence of design projects from a cyclic strategic process and challenges connected to the convergence of design projects into a cyclic tactical process. For all challenges, we analyzed industry practices.

We found three challenges associated with a divergence of design projects from a cyclic process. The coordination of design projects diverging from *platform planning* and *module planning* is difficult due to long project durations, diverse SOPs, and the use of common modules. In industry, coordination is obtained by an early freezing of the platform strategy ("platform launch") and the module strategy ("module fixing"). Furthermore, cross-functional planning teams for *platform planning* and *module planning* and regular reviews by the senior management aim at an alignment with *new vehicle design* and *strategic network design*. However, R&D or marketing dominate these teams (depending on the region); operations only has a minor influence. Additionally, a lack of integration of *process technology design* projects with *platform planning* was discovered across the industry.

In order to diverge *strategic network design* projects from *strategic volume planning*, a mechanism is necessary that coordinates decision making during the multi-year projects with the annually updated long-term forecasts. Manufacturers use a vehicle type-specific

freeze of the central forecast termed "capacity fixing" two years before SOP. They hereby enable an aligned design of capacities, even though the design decisions for the different production stages are made at different points in time. Our analysis of the current industry practice shows a lack of involvement of the operations function in *strategic volume planning*, as only marketing and R&D are involved. Here, a balancing mechanism comparable to the *S&OP* process at the tactical level is missing.

Coordination of *strategic network design* projects converging into *S&OP* is gaining in importance due to the increasing need for alignment between current and future vehicle types in the context of common platforms and modules and the increasing frequency of ramp-ups. This involves the alignment of platform-specific and vehicle type-specific *production network design* with tactical *BP*, vehicle type-specific *sourcing network design* with annual *CSP*, and vehicle type-specific *tactical ramp-up planning* with *MPP*.

For all of these challenges, no firmly established coordination mechanisms could be identified in industrial practice, resulting in a severe lack of transparency and alignment. This is partly due to allocation of planning processes to different parts of the organization. For example, the organization of the procurement department is still structured according to single vehicle types rather than integrated across several vehicle types sharing components or resources. Similarly, the processes for *production network design* projects and the *BP* are historically separated. Furthermore, the IT landscape does not support an integrated perspective. The systems employed for *S&OP* do not link to design projects.

Even though our study on industry practices regarding the integration challenges is based on a large number of OEMs from different regions and market segments, the primary empirical base of our study is limited. Additional studies may be useful in order to strengthen the empirical evidence and refine the analysis. Furthermore, specific integration challenges could be analyzed in more detail or specific aspects of integrated business planning could be reviewed such as the integration of the IT infrastructure or the design of functional incentives to support an integrated view.

Acknowledgment

Chapter 3.

Integrated business planning in the automotive industry: Optimization approaches

In this chapter, a structured review of OR approaches is provided that address the integration challenges identified in the previous chapter. Our review structures OR approaches for the automotive industry with respect to integrated business planning and identifies research gaps. We find that the current literature lacks in the consideration of cross-functional interdependencies. In addition, it disregards the distinctly different characteristics of project planning and cyclic planning.

3.1. Introduction

In this chapter, the gap between research on planning processes in the automotive industry and research on decision making in the automotive industry is bridged. In Chapter 2.3 transparency was generated by the references process for integrated business planning. Furthermore, based on this transparency the resulting integration challenges were identified in Section 2.4.

In this chapter we provide a comprehensive review of OR-based contributions with respect to the identified integration challenges. The review combines the two landscapes of design projects and of cyclic planning and therefore bridges between traditionally

separate research domains. It structures OR approaches for the automotive industry with respect to integrated business planning. We identify shortcomings in the state-of-the-art academic literature and derive future research opportunities.

To accomplish this goal, we used the same methodology as described in Chapter 2 to search for OR approaches with respect to the integration challenges. In total we found 69 relevant publications.

The review is organized on the basis of the classification scheme for integration challenges defined in Section 2.4. First, we focus on the integration of *platform planning* with the diverging design projects (Challenge 1), continue with the integration of *strategic network design* projects diverging from cyclic *strategic volume planning* (Challenge 3) and converging into cyclic *S&OP* (Challenge 4), and terminate with the convergence of *tactical ramp-up planning* projects into cyclic *S&OP* (Challenge 6).

Non-automotive-specific approaches apply without any loss of generality for Challenge 2 and Challenge 5. Because of space limitations, we exclude them from our discussion and refer to the existing reviews on these topics in a general context. For approaches that support *module planning* and its integration with the associated diverging design projects (Challenge 2), we refer to Gershenson et al. (2004), Salvador (2007), and ElMaraghy et al. (2013). For approaches that support *supplier selection*, *make-or-buy*, and their integration with annual *CSP* (Challenge 5), we refer to de Boer et al. (2001) and Weber et al. (1991).

3.2. Diverging cyclic platform planning into design projects

For the challenge of diverging *platform planning* into the early tasks of the associated design projects, the underlying core decision is the multi-platform strategy typically applied by automotive manufactures. It differs significantly from the standard platform approach, in which the entire product portfolio is derived from one common platform (de Weck, 2006). As a result, we focus exclusively on multi-platform approaches applicable in the automotive industry.

The resulting multi-platform problem in *platform planning* at automotive OEMs comprises four central planning decisions:

- Number of platforms: Number/selection of vehicle platforms.

- Vehicle-type-to-platform allocation: Allocation of vehicle types to platforms based on existing set of vehicle types.

- Platform portfolio: Portfolio of vehicle types per platform based on non-existing set of vehicle types.

- Platform selection: Set of components to be included in each platform.

We specifically highlight the difference between optimizing the vehicle-type-to-platform allocation, which is based on a given set of vehicle types, and the platform portfolio, which is derived from scratch. Obviously, a modeling approach can focus only on one of these two decisions exclusively. Approaches that support the platform selection problem for the single-platform case of a product family are not in the scope of this review.

For details on excluded approaches, we refer to existing reviews on the topic of platforms and product family planning in a general context, e.g. in Simpson (2004). In total, we found 19 relevant OR approaches. An overview is given in Table 3.1. Some approaches are non-automotive-specific, but rather consider problem characteristics relevant for the automotive industry.

3.2.1. Diverging into new vehicle design projects

To integrate *new vehicle design* into *platform planning*, the product and market perspective are important in order to analyze the impact of the platform strategy on the *concept design*, estimate the consequences of the customer perception, and trade off revenue effects and scale effects resulting from increased standardization in *target costing*.

Integrating the *concept design* enables the consideration of the commonalities of a platform's vehicle types and the remaining diversification potential. It is characterized by the following decisions:

- Product structure: Dimensions and parts of a vehicle type.

- Product performance: Hard, mechanically measurable product functions, e.g. acceleration or fuel economy.

- Soft attributes: Soft product functions, e.g. style or comfort.

Furthermore, the *concept design* is influenced by the platform architecture, which can be of modular or scalable type. Both may be relevant in an automotive context (cf. Section 2.3.2).

	Decisions in design projects													Problem characteristics													Application		
	Cyclic platform planning decisions				New vehicle design / Concept design			Target costing					PND[a] / LP[c] & SRP[d]			PTD[b] / Product			Operations			Market/sales					Other & approach		
Author (Year)	Number of platforms	Vehicle-type-to-platform allocation	Platform portfolio	Platform selection	Product structure	Product performance	Soft attributes	Development costs	Manufacturing costs	Procurement costs	Investment costs	Revenue[1]	Network locations & structure	Product-to-plant allocation*	Lower level anticipation[2]	Process technology	Platform architecture[3]	Product quality	Time-to-market	Production lead time	Flexibility	Demand volume	Demand uncertainty[4]	Customer valuation[5]	Market competition	Risk	Industry[6]	Planning objective[7]	Modeling approach[8]
Van den Broeke et al. (2017)	☑	☑	☐	☐	☑	☐	☐	☑	☑	☐	☐	-	☐	☐	C	☐	M	☐	☐	☐	☐	☑	D	-	☐	☐	O	DCF	D
Mueller and Haase (2016)	☑	☑	(☑)	☑	☐	☐	☐	☐	☑	☐	(☑)	VP	☐	☐	M	☐	M,S	☐	☐	☐	☐	☑	S	M	☑	☐	O	DCF	D
Hanafy and ElMaraghy (2015)	☑	☑	☑	☐	☑	☑	☐	☑	☑	☑	☐	-	☐	☐	C,L	☐	M	☐	☐	☐	☐	☑	D	-	☐	☐	O	C	D
Van den Broeke et al. (2015)	☑	☑	☐	☐	☑	☐	☐	☐	☑	☐	☐	-	☐	☐	C	☐	M	(☑)	☐	☑	☐	☑	D	-	☐	☐	O	DCF	D
Ramadan and ElMaraghy (2014)	☑	☑	☑	☐	☑	☑	☐	☑	☑	☐	☐	-	☐	☐	M	☐	M	☑	☐	☑	☐	☐	-	A	☐	☐	C	D	O
AlGeddawy and ElMaraghy (2013)	☑	☑	☐	☑	☑	☑	☐	☐	☑	☐	☐	-	☐	☐	C,L	☐	M	☑	☑	☑	☑	☐	-	-	☐	☐	O	CO,O	O
Liu et al. (2011)	☑	☑	☑	☐	☐	☑	☐	☐	☐	☐	(☑)	-	☐	☐	L	☐	S	☑	☐	☐	☑	☐	-	CP	☐	☐	O	CP	D
Sadeghi et al. (2011)	☐	☐	☑	☑	☑	☑	☐	☐	☑	☐	(☑)	VP	☐	☐	-	(☑)	M,S	☐	☐	☑	☐	☑	S	M	☑	☐	O	S	D
Bhandare and Allada (2009)	☑	☐	☑	☐	☑	☑	☐	☐	☐	☐	☐	-	☐	☐	-	☐	S	☑	☐	☐	☑	☑	SS	-	☐	☐	C	C	D
Ben-Arieh et al. (2009)	☑	☐	☑	☐	☑	☐	☐	☐	☑	☐	(☑)	-	☐	☐	M	☐	M	☐	☐	☐	☐	☑	D	-	☐	☐	C,O	P	D
Kumar et al. (2009)	☑	☐	☐	☐	☑	☑	☑	☑	☐	☐	☐	FP	(☑)	☐	C,L	☐	M,S	☐	☐	☐	☐	☑	S	U	☐	☐	C,O	CO,PP	D
Chen and Wang (2008)	☑	☑	☑	☐	☑	☑	☑	☑	☐	☐	☐	-	☐	☐	S	☐	S	☐	☐	☐	☐	☑	S	U	☐	☐	O	CO,PP	D
de Weck (2006)	☑	☑	☐	☐	☑	☑	☐	☐	☑	☐	☐	VP	(☑)	(☑)	M,S	☐	M,S	☐	☐	☑	☐	☐	-	M	☐	☐	O	NPV	D
Jiao and Zhang (2005)	☑	☑	☑	☐	☑	☑	☐	☑	☐	(☑)	☑	VP	☐	☐	-	(☑)	M,S	☐	☐	☑	☐	☑	M	-	☐	☐	O	S	D
de Weck et al. (2003)	☑	☑	☐	☐	☑	☑	☐	☑	☑	(☑)	(☑)	VP	☐	☐	-	☐	M,S	☐	☐	☑	☐	☑	D	CP	☑	(☑)	O	S	D
Seepersad et al. (2002)	☑	☑	☑	☐	☑	☑	☐	☐	☑	☑	(☑)	-	☐	☐	C,L	☐	S	☐	☐	☐	☐	☑	S	-	☐	☐	O	S	D
Morgan et al. (2001)	☑	☑	☑	☑	☑	☑	☐	☑	☑	☑	☑	FP	☐	☐	C	☐	M,S	☐	☐	☑	☐	☑	D	U	☐	☐	O	NPV,P	D
Seepersad et al. (2000)	☑	☑	☑	☐	☑	☑	☐	☑	☐	☑	(☑)	-	☐	☐	C,L	☐	S	☐	☐	☑	☐	☑	SS	-	☑	☐	O	C,L	D
Márkus and Váncza (1998)	(☑)	☑	☑	☑	☑	☑	☐	(☑)	☑	☐	(☑)	VP	☐	☐	-	☑	M	☐	☑	☐	☐	☑	D	M	☑	☐	O	P,U	D

☑ Full consideration (☑) Limited consideration ☐ No consideration

a Production network design.
b Process technology design.
c Location planning.
d Strategic ramp-up planning.

1 FP - fixed pricing, VP - variable pricing.
2 C - capacity, L – layout.
3 M - modular, S - scalable.
4 D - deterministic, S - stochastic, SS - selected scenarios.
5 A - attributes, CP - customer preference, M - monetary value, U - utility.

6 C - car manufacturer, O - other manufacturer.
7 C - costs, CO - commonality, CP - customer preference, D - diversity, DCF - discounted cash out-flow (outflow), L – lead time, NPV - net present value (in and out flows), O - others, P - profit, PP - product performance, U - utility.
8 D - deterministic optimization, O - others, S - stochastic optimization.

* Combines platform-to-plant allocation and vehicle-type-to-plant allocation.

Table 3.1: Overview of OR approaches for platform planning integrating the planning of design projects.

Several examples of an integrated *concept design* can be found among the reviewed approaches. Assuming a modular architecture, Ben-Arieh et al. (2009), Hanafy and ElMaraghy (2014), and Van den Broeke et al. (2015) determine the product structure based on adding or removing modules. Van den Broeke et al. (2017) describe the product performance based on attributes that are supported to a varying extent by different platform design scenarios. Alternatively, de Weck et al. (2003) differentiate platform design and vehicle type design vectors to model the product structure and translate it into the product performance values, which are subject to optimization on the lower level of the two-level approach. Seepersad et al. (2000), Seepersad et al. (2002), and Chen and Wang (2008) follow a similar approach for scalable platforms, but consider the product performance in dedicated constraints with target values or upper and lower bounds.

More complex approaches include the determination of soft attributes into the optimization problem. For example, de Weck (2006) suggests a three-level approach, determining the vehicle type-specific design based on the performance in hard and soft attributes on the lowest level, the platform selection and its design on the second level, and the overall number of platforms and the vehicle-type-to-platform allocation on the top level. Ramadan and ElMaraghy (2014) also consider soft attributes contributing to a specifically defined "platform-diversity-index".

Based on the integrated *concept design*, changed product characteristics resulting from the platform strategy can be considered, such as effects on the product quality. Bhandare and Allada (2009), for example, consider the quality loss due to platforming based on the Taguchi loss function. Thus, the quality loss is evaluated based on the performance loss of the platform solution compared to individually designed products. The performance loss is made comparable by assuming correction costs, e.g. costs of parts or labor needed for potential repairs. Similarly, Kumar et al. (2009) quantify the impact on product quality based on warranty or repair costs.

Furthermore, the integration of the *concept design* enables the analysis of effects on the customer perception, for example based on loss of diversification. Therefore, problem characteristics focusing on the market perspective must also be integrated. The platform strategy's impact on the expected demand volume for the relevant market segments can be captured and further analyzed, assuming the demand uncertainty typically seen in automotive markets. Potential lost revenues can be derived in comparison to individually designed products and the scale effects on the costs can be estimated. The changed volume can be determined based on the customer valuation and on the competition in

a market segment.

Kumar et al. (2009), for example, use an enhanced market segmentation grid, originally defined by Meyer et al. (1997), to capture information not only on the vehicle segments, e.g. family sedan, sports utility vehicle, etc., and the price segments, e.g. high-end, low-cost, etc., but also on the competition in each of these niches. The matrix is converted into a choice tree and used as input for a nested logit model. Another logit model to examine the effect on the customer valuation is given by Jiao and Zhang (2005), based on uncertain demand modeled by the multinomial logit choice rule. Thus, in each market segment, one product (incl. competitor products) is chosen with a certain probability, based on a monetary customer valuation using part-worth values for each of the product performance attributes. An alternative solution method for this formulation is given by Sadeghi et al. (2011). However, Müller and Haase (2016) suggest to change the stochastic model into a deterministic model by adapting the choice probabilities in the multinomial logit formulation. Similar implementations of the part-worth utility concept to incorporate the customer valuation can be found in de Weck (2006), Morgan et al. (2001a), and Márkus and Váncza (1998). Another way of modeling the market competition can be found in the approach by de Weck et al. (2003), in which demand volumes are derived for each vehicle type by benchmarking its performance against the market leader using a "performance-weighted distance".

Knowing the impact of platforming on the demand, the expected financial effects can now be evaluated by integrating *target costing*. Scale effects on costs or lost sales due to the changed customer perception can be derived. Several approaches compute the resulting costs on an aggregate level. Márkus and Váncza (1998), for example, derive the scale effects on the product costs as one joint function of the expected platform volumes. Jiao and Zhang (2005) suggest a "process capability index", which measures the similarity of a new vehicle type to the existing platforms and captures scale effects on aggregate costs, among other measures, by adding a penalty term in case of stronger deviations from the existing platforms. Similar indices are found in Liu et al. (2011), Sadeghi et al. (2011), and Müller and Haase (2016).

However, given a detailed integration of the *concept design*, scale effects can be derived more accurately and broken down into the following components:

- Development costs.

- Manufacturing costs.

- Procurement costs.

- Investment costs.

- Revenue.

For example, de Weck (2006) derives the scale effects on the development costs based on the number of platforms, while the unit and investment costs are modeled using the learning curve concept for the expected vehicle type and platform volumes. The models in Ben-Arieh et al. (2009) and Hanafy and ElMaraghy (2014) account for the development costs of each selected platform and consider purchasing costs and the assembly costs based on the selected platform and additional components required.

A similar cost structure is used in the models suggested by Van den Broeke et al. (2015) and Van den Broeke et al. (2017). However, the broader cost model also considers inventory costs on top of the customization cost. Furthermore, due to synergies in the development process, platforming can shorten the development time for further derivatives of the platform and thus reduce their time-to-market. The two mentioned approaches model the development costs as function of engineering wages and development time accounting for platform design and derivative customization. However, temporal effects, e.g. the opportunity of earlier new product introduction, are not considered.

The impact on the revenue can consider potential pricing adjustments to counteract diversification losses. For example, in Márkus and Váncza (1998) a pricing mechanism is incorporated into an iterative algorithm repeating the interaction between a producer and a customer agent. The producer offers products derived from a set of platforms and sets the product prices according to a defined strategy, e.g. greedy price increase or maximizing the producer's profit. Other approaches use fixed pricing, which means that price effects can only be analyzed based on parameter variations.

3.2.2. Diverging into production network design projects

A platform strategy enables production leveling, increased utilization, and increased responsiveness. The increased responsiveness can be observed in terms of shorter production lead times or increased process flexibility of the production network configuration. Thus, the anticipation of *location planning* and *strategic ramp-up planning* is necessary, including the following decisions:

- Network locations & structure: Production locations and allocation of manufacturing stages.

- Product-to-plant allocation: Combining platform-to-plant and vehicle-type-to-plant allocation, as it is not distinguished in modeling approaches.

- Lower level anticipation: Selected details at lower planning levels, e.g. the capacity level or layout.

For example, de Weck (2006) integrates the decision on the number of plants needed for every platform, which is derived based on a standard plant capacity, and assumes mixed-model assembly for all vehicle types of a platform for the production line layout. Similarly, Kumar et al. (2009) anticipate a mixed-model assembly line for every platform and consider characteristics at lower-level decisions, such as tooling specifications, production plans, and inventory control schemes.

Production lead time effects are considered in Seepersad et al. (2000) and Seepersad et al. (2002), based on the selection of shift models, the number of workers, and the layout of a mixed-model assembly line. Furthermore, Morgan et al. (2001a) introduce detailed capacity and lot sizing constraints in one of their model extensions to analyze the impact on the production lead time. Alternatively, Van den Broeke et al. (2015) capture the impact of platforms on the lead time as reduced safety stock costs due to the resulting pooling. Without modeling any of the associated network decisions, Jiao and Zhang (2005) suggest to evaluate synergies in production lead time based on a "process capability index" assuming larger variations of cycle times in cases of stronger deviations from existing platforms.

The consideration of production flexibility in *platform planning* among the approaches reviewed is mostly based on postponed product differentiation. Ben-Arieh et al. (2009) integrate module-specific and product-specific precedence relations as constraints to anticipate the layout of the assembly line and postpone the product differentiation toward the end of the manufacturing process. AlGeddawy and ElMaraghy (2013) suggest the use of cladograms and liaison graphs to derive a logical assembly sequence and layout based on a modular architecture.

3.2.3. Analysis and research gaps

Table 3.1 shows that most of the reviewed approaches for *platform planning* focus on monetary or customer-related objectives optimizing the number of platforms. Only Jiao and Zhang (2005) and the two related approaches by Sadeghi et al. (2011) and Müller and Haase (2016) do not explicitly capture the number of platforms as a decision. However, they define a "process capability index" to evaluate synergies for a new product based

on its affinity to multiple existing platforms, which makes the approach applicable in a multi-platform setting. The complexity level among the approaches reviewed is very high. Thus, in many cases (meta-) heuristics are used to solve the proposed problems. The vehicle-type-to-platform allocation is preferred to the platform portfolio decision, we assume due to its lower level of complexity. Furthermore, half of the reviewed approaches support the platform selection, which further increases the modeling complexity and is often treated as a sub-problem.

Our analysis shows that state-of-the-art modeling approaches integrate *platform planning* with *new vehicle design*, however, do still offer some areas for improvement. Focusing on *concept design*, only two approaches, namely de Weck (2006) and Ramadan and ElMaraghy (2014), consider the impact of soft attributes when optimizing the multi-platform strategy, i.e. car attributes not technically measurable, but perceived by the customer. This is especially important when a vertically-leveraged platform strategy is applied, i.e. using the same platform for different price segments or brands. Focusing on *target costing*, it can be observed that, even though they are usually named as two important drivers behind platform strategies, the savings effects on development and investment costs are often not considered in sufficient detail. Both should be modeled as functions of the number of platforms and are thus different from the typical scale effects driven by the total production volume.

Besides this, additional product-related effects of the platform strategy are of importance for a comprehensive integration of *new vehicle design*. Synergy effects on time-to-market are not considered by any of the reviewed modeling approaches. Van den Broeke et al. (2015) and Van den Broeke et al. (2017) consider the impact of the platform choice and the resulting customization of each product on the duration of the development, however, they do capture merely the effect on the development costs. Temporal effects, e.g. the timing of new product introduction, are not considered. In times of steadily increasing pressure to shorten development times and lifecycles, this issue must be addressed by future research. For example, approaches based on multi-project planning could be developed.

As more vehicle types are affected, the use of platforms and common parts causes an increasing impact of possible disturbances. Consequently, a thorough analysis of risks must be performed as part of the *platform planning* process, e.g. the risk of unforeseen market dynamics resulting in product portfolio changes in the long-term (as mentioned in Seepersad et al., 2002). A comprehensive risk analysis is so far missing. One example for a source of risk in the globalized car industry is the allocation of common parts to

cheaper suppliers in low-cost countries, as political instability and unreliable processes have an impact on a larger fraction of the product portfolio. Another example is product quality as can be observed in several recent product recalls. Product quality is integrated by only two of the reviewed OR approaches, namely Bhandare and Allada (2009) and Kumar et al. (2009). However, these papers do not perform a risk analysis.

Furthermore, our analysis shows that the integration of *production network design* with *platform planning* is underdeveloped in the state-of-the art approaches. Only two of the modeling approaches in Table 3.1, namely de Weck (2006) and Kumar et al. (2009), integrate the network related decisions in *location planning* and *strategic network planning* to some degree. Considering the impact of the platform strategy on the *production network design* projects, this must be focused by future research. In addition, the synergy effects in operations must be focused on in more detail, e.g. by considering the impact on lead time or process flexibility.

Finally, integration of *process technology design* projects into *platform planning* approaches could not be observed. A few approaches do refer to "product and process platforms", namely Jiao and Zhang (2005) and the related approaches by Sadeghi et al. (2011) and Müller and Haase (2016), as well as Márkus and Váncza (1998). However, neither specifies the term in greater detail. Future research in *platform planning* could, for example, integrate timing restrictions resulting from *process technology design* or restrictions on the availability of process technologies, in order to derive implications on the time-to-market for specific platforms.

3.3. Integration of production network design projects

As discussed in Section 2.4, *production network design* projects require bilateral integration. On the one hand, cyclic *strategic volume planning* diverges into *network design* projects (Challenge 3). On the other hand, *production network design* projects converge into the cyclic *S&OP* process (Challenge 4). We therefore focus on approaches that support *location planning*, *strategic ramp-up planning*, and *capacity planning* in *production network design* projects, and analyze the level of integration with respect to both challenges.

Location planning has the following three key decisions:

- Network locations: Opening or closing of manufacturing plants.

- Network structure: Allocation of the capabilities for each manufacturing stage in

the given network.

- Platform-to-plant allocation: Allocation of each platform to production sites.

Strategic ramp-up planning focuses on the following key decisions for vehicle types of a platform:

- Platform lifecycle plan: Start and end of the production for the vehicle types of a platform.

- Vehicle-type-to-plant allocation: Allocation of vehicle types to manufacturing plants within the plants selected for the associated platform.

Most modeling approaches do not distinguish between platforms and vehicle types and only consider "car models". Thus, we summarize the platform-to-plant and vehicle-type-to-plant allocation decision into the more general product-to-plant allocation.

Capacity planning focuses the following key decisions:

- Technical capacity: Capacity level (annual volume) at each manufacturing stage of a plant.

- Investment plan: Amount and timing of cash flows for investments into production facilities.

- Stage layout: Layout of a manufacturing stage, e.g. spatial arrangement or line balancing.

- Equipment supplier selection: Selected suppliers for the new equipment.

For general approaches, we refer to existing literature reviews, e.g. Melo et al. (2009) or Martinez-Costa et al. (2014). Here, we focus on approaches for the automotive industry. In total we found 29 suitable approaches addressing at least one of the two challenges. An overview is given in Table 3.2.

3.3.1. Diverging cyclic strategic volume planning into network design projects

Based on the discussion in Section 2.4.1, the following modeling requirements support the integration with *strategic volume planning* (Challenge 3). First of all, instead of merely

Table 3.2: Overview of OR approaches for location planning, strategic ramp-up planning, and capacity planning integrating strategic volume planning and S&OP.

Author (Year)	Demand flexibility[1]	Product Scope[2]	Parts commonality	Product life cycles	Production process scope[3]	Sequential decision making	Production network scope[4]	Production flexibility[5]	Efficiency losses[6]	Demand uncertainty[7]	Industry[8]	Planning objective[9]	Modeling approach[10]	Time[11]
Becker et al. (2017)	P	PV			B,F,PA	N	(P)		D	C	NPV	D	D
Liu et al. (2015)	S	MV			B,F,PT	N	V		SS	C	DCF	S	D
Mariel and Minner (2015)	F	MV			-	N	V	-	D	T	DCF	D	D
Koberstein et al. (2013)	S	MV			B,F	N	-	-	S	C	NPV,R	S	D
Lanza and Peters (2012)	F	MV			-	P	V		S	AS	DCF	S	D
Kuhn and Schmausser (2012)	F	MV			B,F,PA	N	(P)	-	SS	C	NPV	D	D
Francas et al. (2011)	S	MV			-	N	(P),V -	S	C	NPV,R	S	D
Hollmann (2011)	S	MV			B,F,PA,PR,PT	N	V	R	S	C	NPV,R	S	D
Schmausser (2011)	F	MV			B,F,PA	N	(P)		SS	C	NPV	D	D
Stephan et al. (2011)	S	MV			-	N	(P),V -	S	T	NPV	S	D
Bihlmaier et al. (2009)	S	MV			B,F,PA,PR,PT	N	V	M,R	SS	C	DCF	S	D
Francas et al. (2009)	S	MV			-	P	-	S	C	DS	S	D
Gneiting (2009)	S	MV			B,F,PA,PR,PT	N	R	S	C	NPV,C	D	D
Kauder and Meyr (2009)	F	MV			-	N	-	SS	C	NPV	D	D
Yang (2009)	S	PV			-	N	-	S	C	NPV	S	D
Bundschuh (2008)	F	PV			B,F,PA	N	(P),V,P	SS	C,AS	DCF	D	D
Friese (2008)	S	MV			F,PT	N	(P),V -	SS	C	NPV	S	D
Kauder (2008)	F	MV			F,PT	N	P,V -	SS	C	DCF	S	D
Roscher (2008)	P	MV			B,F,PA	P	V	M,R	S	C	DCF	D	D
Matta (2007)	S	MV			PT	P	R	S	C	AS	C,P	D	D
Fleischmann et al. (2006)	F	MV			B,F,PA	N	(P),V -	SS	C	DCF	S	D
Chandra et al. (2005)	MV			B,F,PA,PR	N	V	-	S	C	NPV	S	D
Ferber (2005)	F,S	MV			B,F,PA	N	(P),V -	D	C	DCF,NPV	D	D
Graves and Tomlin (2003)	S	MV			B,F,PR,PT	N	P	-	C	F	S	D
Henrich (2002)	F,S	MV			B,F,PA	N	(P)	-	C,P	DS	D	D
Inman and Gonsalvez (2001)	MV			B,F	N	(P)	R	D	C	DS	D	D
Boyer and Leong (1996)	MV			B,F	N	P	M	S	C	Q	D	S
Jordan and Graves (1995)	MV			-	P	-	S	C	DS,Q	D	S
Eppen et al. (1989)	MV			-	N	R	S	C	NPV,R	S	D

Legend:
☑ Full consideration ☑(circled) Limited consideration ☐ No consideration

Production network design decisions — Capacity planning — Decisions in cyclic process — Problem characteristics:
- LP[a] & SRP[b] | Capacity planning | SVP[c] | S&OP[d] (BP[e]) | Product | Operations | Sales | Other | Approach & application

Columns: Network locations | Network structure | Product-to-plant allocation* | Platform lifecycle plan | Technological capacity | Investment plan | Stage layout | Equ. supplier selection | Demand flexibility[1] | Central production plan | Central sales plan | Workforce plan | Product Scope[2] | Parts commonality | Product life cycles | Production process scope[3] | Sequential decision making | Production network scope[4] | Production flexibility[5] | Efficiency losses[6] | Demand uncertainty[7] | Risk | International factors | Industry[8] | Planning objective[9] | Modeling approach[10] | Time[11]

a Location planning.
b Strategic ramp-up planning.
c Strategic volume planning.
d Sales & operations planning.
e Budget planning.

1 F - fulfill, P - postpone, S - shortfall.
2 PV - platform-based vehicle types, MV - multiple vehicle types.
3 B - body shop, F - final assembly, PA - paint shop, PR - press shop, PT - powertrain.
4 N - network, P - plant.
5 P - process flexibility, V - volume flexibility.
6 M - mixed-model production, P - location productivity, R - production ramp-up.
7 D - deterministic, S - stochastic, SS - selected scenarios.
8 AS - automotive supplier, C - car manufacturer, T - (commercial) truck manufacturer.
9 C - costs, DCF - discounted cash out-flow (outflow), DS - demand shortfall, F - flexibility, NPV - net present value (in and out flows), P - profit, Q - production quantity, R - risk.
10 D - deterministic optimization, S - stochastic optimization.
11 D - dynamic, S - static.
* Combines platform-to-plant allocation and vehicle-type-to-plant allocation.

fulfilling the central forecast, OR approaches should consider demand flexibility instruments, which enable a joint optimization of sales and operations on the strategic level. Therefore, mechanisms should be integrated to manipulate the demand, e.g. by considering demand shortfall or postponement. Furthermore, to anticipate future changes of the central production forecast, it is also necessary to consider demand uncertainty.

Several state-of-the-art approaches require demand fulfillment. However, most of them consider demand shortfall. The strict fulfillment is usually necessary in cost minimization approaches, while in profit-maximizing approaches it is common to allow for optional demand shortfall and consider the resulting lost sales. Two approaches exist that consider a temporal shift in demand volumes as delay in the demand fulfillment. Becker et al. (2017) implement lead times in order to consider different ramp-up rates and penalize delays with lower per-unit-turnover to support *strategic ramp-up planning*. Thus, up-front production for markets with long lead times at the beginning of the lifecycle of a vehicle type is possible. Furthermore, Roscher (2008) models delays in demand fulfillment resulting from varying tact time configurations in an approach focused on *capacity planning* of the final assembly stage in an automotive manufacturing plant.

Demand uncertainty is treated in different ways. Several approaches, for example Fleischmann et al. (2006) or Kauder and Meyr (2009) analyze selected scenarios based on a deterministic model, while others use stochastic models, e.g. based on two-stage stochastic programming, as in Bihlmaier et al. (2009) or Francas et al. (2009), or on a MDP, as in Stephan et al. (2010).

Based on demand uncertainty, the investment risk resulting from the sequential decision making in *production network design* projects (cf. Section 2.4.1) can be considered, especially for the *capacity planning* of the four stages in the automotive manufacturing process. Therefore, the (production process) scope of an approach must consider the distinct stages separately. Furthermore, the sequential decision making must be modeled and a suitable risk measure formulated.

Several approaches specifically model the automotive manufacturing stages. For example, Fleischmann et al. (2006) and the related work by Henrich (2002) and Ferber (2005) explicitly define the body shop as vehicle type-specific stage, while the paint shop and final assembly are shared among all products. Moreover, Bundschuh (2008) focuses on powertrain production, specifically modeling stages for the production of engines, transmissions, and axles or the powertrain assembly. Inman and Gonsalvez (2001) explicitly distinguish the body shop and the final assembly line.

Other approaches prefer a generic modeling of sequential production stages. For ex-

ample, Friese (2008) and Bihlmaier et al. (2009), suggest generic production lines, dedicated to selected intermediate products. Thus, network concepts with stages for the same vehicle type being allocated to different sites can be considered, e.g. a CKD production or a central press shop shipping skin parts to several plants around the globe. Similarly, Mariel and Minner (2015) model intermediate products as "product configurations" bound to selected production lines for cab, chassis, and powertrain production and the final assembly in the case of trucks. The "production concepts" suggested by Gneiting (2009) combine production stages with alternative layout concepts. Furthermore, Becker et al. (2017) propose a vehicle type-specific and a generic capacity at each site to reflect dedicated and mixed-model stages. Similarly, Chandra et al. (2005) define "common parts" as parts using the same resources in order to consider the mixed-model production for press, paint, and final assembly shops.

One popular method to consider sequential decision making is the MDP. It is for example used by Stephan et al. (2010) to model sequential decision making for the capacity expansions of a truck manufacturer. Similar approaches in the context of automotive suppliers can be found in Matta et al. (2007) and Lanza and Peters (2012). Furthermore, Schmaußer (2011) outlines sequential decision making with diverse decision time lags in *production network design* projects based on a rolling horizon application of the original mixed-integer linear program (MILP).

The resulting risk can finally be considered by incorporating risk measures. For example, Eppen et al. (1989) suggest a two-stage stochastic program with recourse keeping the expected downside-risk below an upper bound, which is computed as the expected value of the profit being lower than a user-specified target value. Furthermore, Hollmann (2011) and Koberstein et al. (2013) propose to maximize the weighted sum of the expected net present value (NPV) and the CVaR considering multiple sources of risk, e.g. based on uncertainties in demand, exchange rates or costs. Other approaches suggest a post-optimization risk analysis, e.g. based on the value at risk (VaR) in Friese (2008), on the Value at Gain in Yang (2009) or on a robust analysis in Roscher (2008).

3.3.2. Converging network design projects into the cyclic sales and operations planning process

We focus now on the converging of *production network design* projects into the *S&OP* process (Challenge 4). To anticipate the tactical *BP* the following decisions must be integrated:

- Central production plan: Production volume per vehicle type, plant, and period.

- Central sales plan: Distribution/sales volume per vehicle type, region, and period.

- Central workforce planning: Organizational capacity per period.

These tactical decisions are integrated in three different ways. There can be joint optimization in a single-stage program, as for example seen in Fleischmann et al. (2006) and the related work by Bundschuh (2008), Kauder (2008), or Kauder and Meyr (2009). These deterministic models jointly optimize structural decisions on the production network and tactical decisions on the network flow. Other approaches use two-stage or multi-stage programs, thus, the tactical decisions are optimized separately on the lower level, as shown in Eppen et al. (1989), Friese (2008), Bihlmaier et al. (2009) or Francas et al. (2011). A third option is to propose separate approaches for the strategic and tactical level and connect them in an overall planning framework, as in Yang (2009) and Gneiting (2009).

The central production plan is considered in most of the reviewed approaches to a similar extent. Thus, the production volumes are determined based on the product-to-plant allocations and technical capacity levels, ideally for all automotive production stages separately.

The central sales plan, however, is considered in various ways. Some approaches have a limited consideration by anticipating the detailed distribution flow from plants to sales regions, as in Mariel and Minner (2015). Other approaches choose a more detailed modeling by combining the distribution volumes with demand flexibility. For example, Bihlmaier et al. (2009) or Stephan et al. (2010) derive detailed distribution plans to the sales regions and allow demand shortfall.

Workforce planning can be anticipated on a high level using an abstract overtime capacity, which can be used at expensive costs, as found in Fleischmann et al. (2006) or Chandra et al. (2005), or by combining workforce planning with the selection of technical capacity configurations, as seen in Friese (2008) or Mariel and Minner (2015). However, some of the models reviewed allow a more detailed anticipation by including decisions on the workforce level (hiring and layoffs) and the shift model selected, e.g. in Roscher (2008), Bihlmaier et al. (2009) or Francas et al. (2011).

As discussed in Section 2.4.2, the anticipation of *S&OP* decisions is necessary to design the production network's flexibility. Flexibility enables reactions to unknown demand developments and increases the responsiveness. Two types of production flexibility can be distinguished, process flexibility and volume flexibility. Process flexibility describes

the ability to shift various product types between resources (e.g. plants or lines) and is of central concern in *location planning* and *strategic ramp-up planning*. Thus, approaches focusing on process flexibility typically have a broad production network scope. Volume flexibility describes the ability to react to volume fluctuations of a specific product at a facility without any additional construction or investment and is important in *capacity planning*. To design the production flexibility, among other problem characteristics, the demand uncertainty and the production process scope again play an important role (as already discussed in the previous Section 3.3.1).

A popular concept of process flexibility, "chaining", is introduced in the fundamental approach by Jordan and Graves (1995). A "chaining" structure is characterized by an unbroken chain built by all the links between products and sites resulting from the product-to-plant allocation and is known as a very efficient *network design* to achieve process flexibility. Boyer and Leong (1996) further analyze process flexibility and the effect of reduced efficiency in mixed-model production and find the *network design* based on "chaining" to be superior. Graves and Tomlin (2003) define an index to measure process flexibility in a multi-stage *production network design* with a large number of products and stages. Francas et al. (2009) analyze the robustness of "chaining" for cases of additional variability during product changeovers by implementing additional constraints on the number of links between vehicle types and plants. Kauder and Meyr (2009) suggest additional "chaining" constraints examining the links between all possible subsets of products and all possible subsets of plants. However, they conclude that the solution of real world problems becomes difficult due to the increased complexity. Thus, a heuristic to solve the problem more efficiently is derived in Kauder (2008).

Volume flexibility can be achieved by different levers considered in *capacity planning*. One option is the implementation of capacity reserves, so the model incorporates a certain level of slack capacity, as for example shown by Chandra et al. (2005) or Fleischmann et al. (2006). Another lever for volume flexibility is the integration of organizational measures. This can be additional capacity resulting from overtime, i.e. leading back to the anticipation of workforce planning. Similarly, workers can be transferred between lines or plants, as proposed by Friese (2008) and Francas et al. (2011), or temporary workers can be hired, as proposed by Roscher (2008) and Francas et al. (2011). It is also possible to anticipate changes in tact times, as seen in Roscher (2008) and Liu et al. (2015).

Furthermore, as discussed in Section 2.4.2, the integration with *S&OP* aims at a higher accuracy in *capacity planning* based on the consideration of synergies or complexities caused by other products. Relationships and commonalities between the products based

on the product strategy should thus be considered. The product scope should be tailored to platform-based vehicle types, as for example in Bundschuh (2008), suggesting product groups depending on the production process, or as in Becker et al. (2017), explicitly distinguishing platforms and vehicle types in a multi-platform strategy. Furthermore, parts commonality across all vehicle types should be considered to account for the scale effects of the module strategy. Many modeling approaches therefore use a generic bill of materials (BoM). In Gneiting (2009), for example, preassembly lines for modules are considered based on a generic BoM. Furthermore, in Mariel and Minner (2015) a specific BoM concept is introduced to account for detailed duty obligations.

More complexities on the shop floor are caused by production ramp-ups of new vehicle types. An integrated approach must thus consider product lifecycles and the changed conditions during the different lifecycle phases. Inman and Gonsalvez (2001), for example, focus on improving the capacity utilization during product changeovers. Furthermore, Francas et al. (2009) analyze the network's process flexibility under lifecycle demand.

Based on the consideration of product relationships and lifecycles, the effects on the efficiency in production can be accounted for as efficiency losses. For example, in Bihlmaier et al. (2009) ramp-up effects are considered by lowering the capacity in the first production period, as well as inefficiencies for mixed-model production. Furthermore, Roscher (2008) implements learning effects in a separate model capturing efficiency losses after line reconfigurations.

Finally, international factors are important for the integration of *S&OP* in *production network design*, as they influence the distribution costs and, thus, the *network design*, especially with the increased standardization resulting from platform and module strategies. Local content requirements and exchange rates are often implicitly considered in the distribution cost rates, as for example in Kauder and Meyr (2009). Furthermore, Fleischmann et al. (2006) propose a model extension to incorporate taxes and Mariel and Minner (2015) consider duty drawbacks in *location planning*.

3.3.3. Analysis and research gaps

From a *production network design* perspective, most of the approaches in Table 3.2 support *location planning*, *capacity planning* or both in a joint approach. Most approaches use a dynamic time representation with a long planning horizon. The dominant planning objective is cash flow optimization.

Furthermore, our analysis shows a lack in supporting some of the relevant decisions for

automotive *production network design*. There are only a few OR approaches that fully support the network locations and network structure decisions in *location planning*. In *capacity planning*, the detailed investment plan is rarely considered. Even though many approaches use cash flows, the exact timing of the flows is often neglected. Furthermore, the three approaches supporting the stage layout decision, namely Bundschuh (2008), Gneiting (2009), and Schmaußer (2011)[1] are doctoral theses with a very broad scope. As there is dedicated literature on layout design, it appears that the layout decision is considered as a separate problem in the academic literature. Similarly, the decision on the equipment supplier selection is not supported in the literature reviewed. Further research should analyze whether there are adequate modeling approaches in other literature streams. Furthermore, we found only one approach supporting *strategic ramp-up planning*, namely Becker et al. (2017). However, as the trend in the automotive industry is moving toward more flexible lifecycles, further research is necessary on the optimization of platform lifecycle plans.

From the perspective of integrating *production network design* with *strategic volume planning*, future research should focus on the impact of demand flexibility instruments to manipulate the demand, e.g. a more flexible shifting of demand volume to earlier or later periods. However, for such an approach, the granularity of the planning periods must be sufficiently detailed. Accordingly, both approaches identified with such a feature, namely Becker et al. (2017) and Roscher (2008), use monthly periods. In this context, future approaches could also aim at intensifying the integration of *demand planning*. For example, the impact of integrating long-term revenue management could be examined, including pricing and marketing strategies along the lifecycle of a vehicle type.

Furthermore, future research should study the sequential decision making in *capacity planning* of the automotive manufacturing process with decision time lags and annually updated forecasts. Existing approaches modeling sequential decision making based on uncertain demand updates, namely Matta et al. (2007), Stephan et al. (2010), and Lanza and Peters (2012), focus on a different context, i.e. the planning of capacity expansions. However, for *capacity planning* in *production network design* projects, it is important to consider the different time lags for the manufacturing stages of an OEM, the diverse SOPs of vehicle types sharing capacities, and the investment risk resulting from lost sales or unused capacities over the lifecycles.

From the perspective of integrating *S&OP*, it can be concluded that most approaches anticipate network flows, at least in production. On the sales side, there are modeling

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[1]Kuhn and Schmaußer (2012) is based on the same modeling approach

approaches incorporating distribution flows combined with limited demand flexibility. However, real measures are not anticipated. Workforce planning is strongly focused on a high-level anticipation of shift models, which enables the consideration of volume flexibility. However, an extended workforce planning leads to a more accurate representation of volume flexibility and, thus, a better estimation of available real capacities. Only a few OR approaches show an increased granularity level for workforce planning, e.g. by adding temporary workers or transferring workers between facilities. Similarly, anticipated line reconfigurations like tact time changes are rarely considered in the state-of-the-art literature. Focusing on process flexibility, it can be concluded that there are attempts to implement advanced process flexibility concepts like "chaining" in *production network design*, however, due to complexity reasons, most approaches rely on a limited consideration.

Furthermore, to support the integration of *S&OP*, future research needs to focus on a broader and more realistic modeling of the products. Thus, new approaches should target the detailed modeling of vehicle types based on platforms and parts commonality, in order to consider scale effects and interdependencies of the platform and module strategies. In the globalized car industry, typical international factors such as tariffs, taxes, and regional risks must also be incorporated for a realistic modeling of the costs and risks associated with the allocation of common parts.

3.4. Converging tactical ramp-up planning projects into cyclic sales and operations planning

As existing OR approaches focus either on cyclic *S&OP* or on *tactical ramp-up planning*, we first study the requirements for OR approaches supporting the conventional *S&OP*, before we discuss additional requirements for converging *tactical ramp-up planning* into *S&OP* (Challenge 6) and derive the future research directions.

For general approaches supporting *BP* and *MPP* we refer to other reviews, e.g. Mula et al. (2010) or Esmaeilikia et al. (2016). For *tactical ramp-up* we refer to Surbier et al. (2013) or Glock and Grosse (2015). Here, we focus on approaches for the automotive industry. In total we found 21 suitable approaches. An overview is given in Table 3.3.

Table 3.3: Overview of OR approaches for budget planning, master production planning, and tactical ramp-up planning.

Author (Year)	Reallocation (BP[b])	Central production plan (BP[b] & MPP[c])	Central sales plan	Workforce plan	Detailed ramp-up curve (TRP[d])	Market launch scheme	Product Scope[1]	Parts commonality	Product life cycles	Production process scope[2]	Production network scope[3]	Supply chain uncertainty[4]	Process flexibility instruments[5]	Volume flexibility instruments[6]	Lead times	Inventory	Ramp-up effects	Demand uncertainty[4]	Demand flexibility instruments[7]	Fairness across sales regions	International factors	Cyclic planning[8]	Industry[9]	Planning objective[10]	Modeling approach[11]	Time[12]
Wochner et al. (2016)	□	☑	☑	□	□	☑	VO	□	☑	F	N	D	-	-	☑	☑	☑	D	E,P,S	☑	□	-	C	C,DS	D	D
Laurent Lim et al. (2014)	□	(☑)	(☑)	☑	□	□	SV	□	□	-	L	D	-	SS	☑	☑	☑	S	E,P	□	□	F,R	C	DCF	D	D
Hemig et al. (2014)	□	☑	□	☑	□	□	MV	□	□	F	L,P	D	-	OT,P,S,SS,T,W	☑	☑	☑	D	E,P	□	□	C	C	D	D	D
Wittek (2013)	☑	☑	□	☑	□	□	MV	☑	□	F	N	D	T	OT,S	☑	☑	(☑)	SS	E,P,S	□	(☑)	F,R	C	P	D	D
Wittek et al. (2012)	☑	☑	□	☑	□	□	MV	□	☑	F	N	D	T	OT,S	☑	☑	☑	SS	E,P,S	□	□	F,R	C	P	D	D
Garcia-Sabater et al. (2011)	☑	☑	(☑)	☑	□	□	(MV)	☑	□	PT	N	D	-	OT,S,SS,T	☑	☑	□	D	E,P	□	□	F,R	AS	C,S	D	D
Kabak and Ülengin (2011)	(☑)	☑	□	☑	□	□	MV	☑	☑	B,F,PR	N	F	OS	OS	☑	□	□	F	S	□	□	-	T	F	D	S
Sillekens et al. (2011)	□	☑	□	☑	□	□	MV	☑	□	B,F,PA	L	D	-	OT,P,SS,S,T,W	☑	☑	□	D	E	□	□	F,R	C	C	D	D
Wittek et al. (2011)	☑	☑	□	☑	□	□	MV	☑	☑	F	N	D	T	OT,S	☑	☑	□	SS	E,P,S	□	□	F,R	C	NPV	D	D
Zhang et al. (2011)	□	☑	□	☑	□	□	MV	□	□	B,F,PA,PR	L,P	F	-	-	☑	☑	□	S	S	□	□	-	C	P,DS	F,S	D
Hemig (2010)	□	☑	□	☑	□	□	MV	☑	□	B,F,PA	L,P	D	-	OT,P,S,SS,T,W	☑	☑	□	D	E,P	□	□	C	C	DCF	D	D
Peidro et al. (2010)	□	☑	☑	(☑)	□	□	(MV)	☑	□	F	N	F	-	OT	□	☑	□	F	E,P	□	□	R	C	F	D	D
Peidro et al. (2009)	□	☑	☑	(☑)	□	□	(MV)	☑	□	F	N	F	-	OT	☑	☑	□	F	E,P	□	□	R	AS	C	F	D
Torabi and Hassini (2009)	□	☑	□	☑	□	□	MV	☑	□	F	N	F	-	SS	☑	☑	□	F	E	□	□	-	C	C,DS	F,D	D
Askar (2008)	☑	☑	☑	☑	□	□	MV	☑	□	B,F,PA,PT	L,P	D	-	OT,P,S,SS,T,W	☑	☑	□	D	E,P	□	□	R	C	DCF	D	D
Sillekens (2008)	□	☑	□	☑	□	□	MV	☑	□	B,F,PA	L,P	D	-	OT,P,S,SS,T,W	☑	☑	□	D	E	□	□	F,R	C	C	D	D
Askar et al. (2007)	□	(☑)	☑	□	□	□	MV	☑	□	B,F,PA,PT	D	D	-	OT,P,S,SS,T,W	☑	☑	□	D	E,P	□	(☑)	F,R	C	DCF	D	D
Biller and Swann (2006)	□	☑	☑	□	□	□	MV	□	□	F,PT	N	D	-	-	☑	☑	□	D	RM	□	□	C	C	P	D	S
Biller et al. (2005)	□	(☑)	(☑)	□	□	□	SV	□	□	-	P	D	-	-	□	☑	□	SS	RM	□	□	-	C	D	D	D
Gnoni et al. (2003)	(☑)	☑	□	□	□	□	(MV)	☑	□	-	N	S	T	-	☑	☑	□	D	E,P	□	□	R	C	D	D	D
Escudero et al. (1999)	□	☑	☑	□	☑	☑	PV	☑	(☑)	F	S	-	-	OS,SS	☑	☑	□	S	E,P,S	☑	□	R	C	C,DS	S	D

☑ Full consideration   (☑) Limited consideration   □ No consideration

a   Sales & operations planning
b   Budget planning
c   Master production planning
d   Tactical ramp-up planning.

1   MV - multiple vehicle types, PV – platform-based, SV - single vehicle type, VO - vehicle type with options.
2   B - body shop, F - final assembly, PA - paint shop, PR - press shop, PT - powertrain.
3   L - line, N - network, P - plant.
4   D - deterministic, F - fuzzy, S - stochastic, SS - selected scenarios.
5   S - subcontracting, T - technical adjustment.
6   OS - outsourcing, OT - overtime, P - personnel level (hiring/layoffs), S - shift model, SS - safety stock, T - tact time, W - working time account.
7   E - expedite, F - fulfill, P - postpone, RM - revenue management, S - shortfall.
8   F - frozen horizon, R - rolling horizon.
9   AS - automotive supplier, C - car manufacturer, T - (commercial) truck manufacturer.
10 C - costs, DCF - discounted cash flow (outflow), DS - demand shortfall, NPV - net present value (in and outflows), P - profit, S - stability.
11 D - deterministic optimization, F - fuzzy optimization, S - stochastic optimization.
12 D - dynamic, S - static.

3.4.1. Cyclic budget planning and master production planning

In *BP* and *MPP* the nature of the key decisions is similar, however, based on different granularity levels and horizons for the annual and monthly cycle, respectively:

- Central production plan: Production volume per vehicle type, plant, and period.

- Central sales plan: Distribution/sales volume per vehicle type, region, and period.

- Central workforce plan: Organizational capacity per period.

- Reallocation plan (*BP* only): Timing of the reallocation of a vehicle type to another plant within the given flexibility of the production network.

As discussed in the previous sections, cyclic *S&OP* is a central task covering all vehicle types of the OEM with increasing granularity level during the last few months before the DOP and must consider product related effects, e.g. synergy and scale effects or loss of efficiency. Hence, the product scope of OR approaches should focus on multiple vehicle types, as it can be observed in most of the approaches in Table 3.3. Besides this, other product-related details need to be considered. Escudero et al. (1999) model products in product groups resembling a platform-based relationship. Wochner et al. (2016) focus on a single vehicle type, however, differentiate between engine variants and other selected options. Similar to the discussion in Section 3.3.2, a generic BoM can be used to account for parts commonality across vehicle types, as seen in Escudero et al. (1999) or Garcia-Sabater et al. (2011).

In addition, the scope should consider the distinct automotive production stages and all production plants of the OEM. Global approaches, such as Kabak and Ülengin (2011) or Zhang et al. (2011), simultaneously optimize several production stages network-wide, taking into account granularity losses, while local, sequential approaches, such as Askar et al. (2007) or Sillekens et al. (2011), are limited to one plant and optimize the stages sequentially with a higher level of detail. Even though being too narrow in scope, sequential approaches are relevant in *S&OP*, as they can be combined with a global approach, for example to determine more detailed workforce plans.

To support a more realistic modeling of the production network's responsiveness in *S&OP*, several problem characteristics are important, such as uncertainty, flexibility instruments, production lead times, and inventory levels.

Supply chain uncertainty is important on the tactical level and complements the demand uncertainty. Examples are uncertain production and procurement costs, as in

Escudero et al. (1999) or Zhang et al. (2011), processing times and breakdowns, as in Gnoni et al. (2003) and Peidro et al. (2010), or real capacity levels, as in Torabi and Hassini (2009). As exact probability distributions are often unavailable, fuzzy numbers can be used instead, as seen for example in Peidro et al. (2009).

Based on the boundaries defined by the platform strategy and the production network design, the use of the resulting flexibility instruments is subject of *S&OP*. Process flexibility instruments focus on the entire network and support the reallocation in *BP*. For example, Wittek (2013) and Wittek et al. (2011) model the mid-term reallocation based on technical adjustments within a flexible automotive production network. Gnoni et al. (2003) allow product-specific set-ups to reallocate products and intermediate products within the production network of an automotive supplier. Kabak and Ülengin (2011) integrate the optional subcontracting of intermediate products to external contractors, i.e. the mid-term reallocation from an internal line to a contractor, for the setting of a truck manufacturer.

Volume flexibility instruments are plant-specific and temporarily increase the effective capacity. For example, Askar et al. (2007) or Sillekens et al. (2011) combine tact time variations with organizational flexibility instruments. Escudero et al. (1999) consider partial outsourcing of subassemblies and Lim et al. (2014a) determine safety stock levels to generate additional capacity over the medium term.

Organizational flexibility instruments are linked to workforce planning, which is considered in different ways in the state-of-the-art approaches. Models exist that incorporate limited workforce planning without any detailed selection of shift models or adjustment of workforce levels, e.g. Peidro et al. (2010) confine their model to the determination of overtime and idle times. A more detailed modeling of organizational measures supporting the shift model selection, e.g. by defining the number of shifts per day or extra shifts on the weekend, is suggested by Garcia-Sabater et al. (2011) at the second stage of their two-stage approach for *MPP*. The highest level of detail in modeling workforce planning and organizational volume flexibility instruments is found in approaches limiting the scope to the plant level. For example, Askar et al. (2007) and Askar (2008) incorporate the detailed shift model selection and the optional hiring or layoff of workers. In a similar approach Sillekens et al. (2011) consider the use of working time accounts. The approach is further examined as aggregate planning approach for the body shop, paint shop, and final assembly shop of a plant in Sillekens (2008), enabling the transfer of workers between stages. A further extension allowing the transfer of workers between parallel lines in an automotive production plant, is given by Hemig et al. (2014) and,

taking the body and paint shop into account, by Hemig (2010).

Additional flexibility can be generated in sales. Thus, modeling approaches need to enable the use of demand flexibility instruments in *S&OP*. Sales volumes can be shifted between periods as shown in Wittek et al. (2012) and Wittek (2013). Thus, production can be expedited and the products stored as inventory or it can be postponed, leading to potential lost sales. Alternatively, a share of demand for a specific vehicle type can be substituted, as shown in Wochner et al. (2016). Furthermore, revenue management is an important flexibility instrument in *S&OP*. It can be applied as dynamic pricing approach and, consequently, impacts the associated sales plan. In Biller et al. (2005), dynamic pricing is based on a make-to-order setup, in which a vehicle type is ordered by the customer at a price set by the manufacturer and demand is derived as a non-increasing function of the price. Similarly, Biller and Swann (2006) suggest a dynamic pricing approach with segment-dependent pricing based on linear demand functions derived from demand cross-elasticity to directly imply the resulting sales volume, however, neglect the distribution flows.

Since responsiveness means adjusting to changes quickly, it is not enough to focus on flexibility instruments only. Suitable OR approaches should also incorporate lead times and inventory in order to consider time implications in *S&OP*. A reallocation triggered by cheaper production costs could, for example, imply longer lead times, however, might be offset by additional buffers or safety stock. Furthermore, long distant sourcing makes it important to account for transportation times, as suggested in Lim et al. (2014a). Thus, the tracking of shipments in progress and of inventory balances is necessary to account for lead time implications, as seen in Peidro et al. (2010) and Torabi and Hassini (2009).

Finally, approaches that support cyclic *S&OP* should also consider the cyclic planning character by applying rolling horizon and frozen horizon mechanisms, as for example seen in Lim et al. (2014a) or Garcia-Sabater et al. (2011).

3.4.2. Converging tactical ramp-up planning projects

In every *tactical ramp-up planning* project the following two key decisions are made:

- Detailed ramp-up curve: Ramp-up pattern of production volumes of the new vehicle type.

- Market launch scheme: Timing and volumes of the introduction per market regions.

These decisions are directly linked to the product lifecycles. Thus, if these ramp-up decisions are not integrated, the product lifecycles at least must be systematically captured in order to support convergence into *S&OP*. Therefore, the demand profiles must reflect the different lifecycle phases, i.e. low demand at the end of a lifecycle and high demand at the beginning, as shown in Wittek (2013).

Integrated approaches must consider the different strategies of how to manage a ramp-up of a new vehicle type. Wochner et al. (2016) suggest an approach for the prompt change-over, i.e. the old vehicle type is ramped-down completely, before the ramp-up of the new vehicle type is initiated, and derive the optimal ramp-up curve. Another strategy seen in the automotive industry is an overlap phase, during which the new vehicle type is already being produced and held as inventory or shipped only to certain markets, while the old model is still ramped-down in parallel.

Furthermore, the impact of the increased complexity during the ramp-up must be considered, e.g. by assuming reduced capacity after a change of the production settings, as shown in Askar et al. (2007) for tact time changes. Alternatively, the reduced capacity can be modeled by introducing a discrete set of capacity excess levels reflecting the expected level of complexity during the ramp-up phases, as proposed by Wochner et al. (2016).

In addition, the dynamics of "gray markets" based on unintended trades between regions during the ramp-up phase must be prevented. This can be supported by the consideration of fairness across sales regions, e.g. based on region-specific fill-rates for the market launch scheme, as shown in Wochner et al. (2016).

3.4.3. Analysis and research gap

Most approaches in Table 3.3 target monetary objectives, i.e. profits, costs or cash flows, and are based on a dynamic time representation with a high planning frequency and granularity. Other important mid-term objectives, such as the stability of production plans or customer satisfaction, are considered in just a few approaches based on multi-objective programming, namely Escudero et al. (1999), Torabi and Hassini (2009), Zhang et al. (2011), Garcia-Sabater et al. (2011), and Lim et al. (2014a). Future research has to include an analysis of the specific trade-offs resulting from the integration of *tactical ramp-up planning* into *S&OP*, e.g. of the trade-off between costs and ramp-up speed or time-to-market.

Furthermore, our analysis shows a clear focus of the literature on the cyclic *S&OP* tasks, i.e. OR approaches supporting *MPP* and *BP*. For *tactical ramp-up planning* only

one approach, namely Wochner et al. (2016), was found, which supports the associated decisions, i.e. the detailed ramp-up curve and the market launch scheme, for the case of one vehicle type ramped up on a dedicated production line. Due to the increased importance of the ramp-up problem in the automotive industry, broadening the academic contribution must be a major concern. However, having already highlighted the need for integration with cyclic *S&OP*, an extension of the scope is necessary resulting in a challenging research gap. Thus, OR approaches are needed supporting a joint optimization of ramp-up curves and market launch schemes for new vehicle types as well as central sales and production plans for the existing vehicle types. The appropriate level for the integration of *S&OP* with *tactical ramp-up planning* is the *MPP* task, leading to a clear hierarchy with *strategic production network design* tasks, i.e. *location planning*, *strategic ramp-up planning*, and *capacity planning*, converging into *BP* on a long-term level and *tactical ramp-up planning* converging into *MPP* on a more detailed level.

Additionally, state-of-the-art approaches in *S&OP* do not consider several characteristics important for the integration of ramp-up planning, such as product lifecycles, efficiency losses, and fairness across sales regions.

Focusing on the cyclic *S&OP*, our analysis shows that existing OR approaches mostly focus on operations. Just a few approaches support the joint determination of a sales plan specifying the detailed distribution volumes from plants to regions and enabling more demand flexibility such as postponing and expediting of demand. Furthermore, revenue management is only considered in two approaches as demand flexibility instrument, namely in Biller et al. (2005) and Biller and Swann (2006). However, more contributions focusing on a joint optimization of sales and operations plans are necessary in order to further push for a balanced *S&OP* process at automotive OEMs.

Our analysis further shows that only Wittek (2013) and related publications fully consider the reallocation decision in *BP*. Consequently, there is a lack of modeling process flexibility instruments in state-of-the-art literature. Only Gnoni et al. (2003), Wittek (2013), and the related publications incorporate the mid-term adjustment of the technical capacity. Besides Kabak and Ülengin (2011), who suggest mid-term contracting of subassemblies, no other process flexibility instruments enabling reallocation (such as the training of workforce) are considered. Therefore, due to the current development toward a higher level of process flexibility, the use of associated flexibility instruments must be focused by OR approaches supporting *BP*.

A detailed consideration of volume flexibility instruments in *S&OP* can mostly be observed for sequential approaches. Global approaches, in contrast, do not usually

model the individual volume flexibility instruments, but rather consider their aggregate effect.

Furthermore, our analysis shows that the concept of multi-platform-based vehicle types has not been addressed. Thus, future research must explore opportunities to better support platform-based planning across multiple vehicle types and focus on a realistic modeling of platforms.

The modeling of parts commonality is more advanced. Many approaches suggest a product structure based on a generic BoM. However, as discussed in Section 3.3, a realistic modeling of costs and risks associated with the allocation of common parts requires also the consideration of typical international factors such as tariffs, taxes, and regional risks. Despite their importance for the globalized car industry, this is currently missing.

3.5. Conclusion

Based on the reference process for integrated business planning and the resulting integration challenges discussed in Chapter 2, we have provided a comprehensive review of 69 OR approaches supporting integrated business planning for automotive OEMs in this section. Besides the research gaps identified for the integration challenges in Sections 3.2.3, 3.3.3, and 3.4.3 we have observed two generic findings.

First, our analysis shows that the focus of research has been on standard problems. The contributions aim at supporting individual processes and lack in the consideration of cross-functional interdependencies. To name just a few opportunities, future research should focus on OR approaches that support the integration of *production network design* and *process technology design* into *platform planning* and that consider demand flexibility instruments for a better integration of *strategic volume planning* and *production network design*.

Second, state-of-the-art OR approaches disregard the distinctly different characteristics of project planning and cyclic planning. There are many opportunities for methodological developments. For example, to support *platform planning* and the integration with the diverging design projects, approaches based on multi-project planning could be developed that aim to reduce time-to-market. Another example is the determination of the platform lifecycle plans as a result of *strategic ramp-up planning* and its integration with *MPP*. In addition, future OR approaches need to capture the sequential decision making with time lags during design projects.

Bridging the findings of Chapters 2 and 3 to evaluate the status of integrated business planning in the automotive industry, we find many development opportunities. In practice, OEMs have recognized the need for a structured integrated business planning process (as discussed in Section 2.5). Manufacturers react to integration challenges connected to diverging projects from cyclic strategic processes by an early fixing of decisions. This mechanism aims at achieving coordination by providing a consistent planning basis, but has a substantial negative impact on the flexibility of OEMs. Alternative mechanisms could be implemented, making use of dynamic decision support that still considers the nervousness of central strategies. Also, there is a substantial improvement potential for coordination mechanisms, organizational structures, and supporting planning systems, especially for the integration challenges connected to the converging into *S&OP*.

Academic literature suffers largely from the same shortcomings. The state-of-the-art literature is focused on individual processes rather than on the integration challenges. Especially the integration challenges connected to the diverging of *production network design* and *process technology design* from *platform planning* and to the convergence of *tactical ramp-up* projects into *S&OP* offer many opportunities.

However, there is also innovative work. For the integration challenge connected to the convergence of strategic *production network design* into tactical *BP*, academic approaches under suggestion offer integration mechanisms, which may provide guidance for practitioners.

In summary, integrated business planning is a new field offering a number of new research opportunities and linking traditionally separate research fields like product design, network design, and network planning.

Acknowledgment

Chapter 4.

Time-phased capacity planning in the automotive industry

Construction and equipment procurement lead times amount to several years and strongly vary across the stages in the automotive manufacturing process. Some stages require equipment tailored to each of the vehicle derivatives that have varying start of production dates. Due to the long lead times, demand is highly uncertain. Demand forecasts are thus updated in an annual process. Consequently, manufacturers have to make time-phased decisions about capacity configurations based on changing demand information. This chapter identifies the key interactions between capacity planning projects and the cyclic forecasting process and provides an innovative planning approach. Our approach combines a Markov decision process with a mixed-integer linear program. The cyclic forecasting process is considered through Bayesian updating. To capture risk attitudes, we adapt the decomposition of the conditional value at risk. For a typical capacity-planning problem instance, we show our approach's superiority over conventional stochastic approaches. We also determine the performance loss caused by the wide-spread practice of early central capacity fixing. Finally, manufacturers currently consider to introduce flexible body shops that can be shared by different derivatives leveraging the enhanced vehicle modularization. We show that this flexibility on the operative level comes at significant hidden cost resulting from lost decision flexibility.

4.1. Introduction

Automotive manufacturers invest heavily in production capacities. Globally, two out of three investment projects in the automotive industry are production related. The number of production-capacity projects grows by more than ten percent annually (Ernst & Young, 2015b). The reasons for this development are manifold. Most importantly, the number of new product introductions is constantly increasing due to broader product portfolios and shorter product lifecycles. The increased frequency of new car-model introductions requires commensurate investments in production capacity. In response to these developments, the industry introduces modular vehicle platforms, which enhance pooling. Many manufacturers, for instance, are currently considering the replacement of dedicated body shops with a single, flexible body shop, in which all derivatives of the same platform are manufactured.

Increasing digitalization and other technological advances are also transforming the automotive manufacturing process and forcing manufacturers to invest more heavily in new, often more expensive equipment. Furthermore, ongoing localization of production ensures that automotive manufacturers will stay focused on capacity planning. The increase in production volume required in countries such as China, India, and Mexico is far larger than the planned, already substantial capacity growth in these regions. Additional capacity expansions will thus be necessary (Dharmani et al., 2015).

Automotive manufacturers plan and realize new capacities whenever new vehicle models are introduced. For each derivative of a new vehicle model, they define a separate project to configure the manufacturing process at a selected site. The timing of such a project depends heavily on the derivative's SOP and stretches over several years. Capacity extensions after SOP are extremely costly. Output is instead adapted through changes in operating mode such as the choice of suitable shift models. During the project, the manufacturer has to decide on the capacity configuration for the different stages in the manufacturing process, i.e. press shop, body shop, paint shop, and final assembly. These decisions must be made with different lead times and interact across projects. The investment problem thus involves multiple, time-phased decisions for multiple derivatives. The decisions are made based on demand forecasts, which are updated in a cyclic process. Hence, volume and model mix uncertainties cause demand information to fluctuate for time-phased investment decisions. The uncertainties combined with the large investment costs engender substantial investment risk.

In practice, automotive manufacturers take a rather pragmatic approach to handle the

challenges associated with time-phased decision making in capacity planning projects. They apply central capacity fixing by freezing the configuration of all manufacturing stages long before a derivative's SOP. They thereby ensure capacity alignment across manufacturing stages. However, they also diminish their flexibility to react to market developments.

The academic literature on capacity planning in the automotive industry proposes two-stage stochastic programming to capture uncertainty. However, such methodology is incapable of capturing the dynamic character of time-phased decision making. Generic approaches to dynamic capacity planning focus on capacity adjustments during lifecycles rather than on time-phased capacity projects before SOP.

In this chapter, we provide the following contributions. We structure automotive capacity planning by identifying interactions between (i) capacity-planning projects for different derivatives of a new vehicle model, as well as (ii) time-phased decision making within these projects and cyclic forecasting. A dynamic-programming approach based on an MDP to support time-phased decision making in capacity planning projects is developed. Bayesian updating is employed, to take into consideration information updates from the cyclic forecasting process that become available during the course of the capacity planning projects. For time-consistent representation of the investment risk, the decomposed CVaR is adapted for the MDP approach.

Our analysis shows the superiority of the proposed approach over state-of-the-art methodologies for capacity planning projects with time-phased decision making. The numerical results show especially pronounced benefits, if manufacturers are risk-averse or if they face a volatile environment. Here the approach exploits the possibility of selecting different capacities over the course of the project, which are later aligned by a flexible use of operating modes.

Our analysis shows that the current industry practice of central capacity fixing entails substantial inefficiencies, which depend on the risk attitude. Our analysis also shows that the current industry trend toward flexible body shops incurs hidden costs caused by reduced decision-making flexibility. The need to determine capacity earlier diminishes the benefit of capacity pooling.

In Section 4.2, we give an overview of the relevant literature. In Section 4.3, we define the specific problem of time-phased decision making in capacity planning projects. In Section 4.4, we present the associated modeling approach. In Section 4.5, we discuss the findings of our analysis. In Section 4.6, we give a conclusion and derive managerial implications.

4.2. Literature review

Modeling capacity planning in the automotive industry has been a popular research field over the last 15 years (Volling et al., 2013). Two different types of modeling approaches are distinguishable: dedicated approaches and integrative approaches. Details on integrative approaches can be found in the given review paper.

Dedicated approaches focus solely on capacity-configuration optimization, assuming a given manufacturing network, focus plant, or selected manufacturing lines. Relatively low model complexity thus enables demand uncertainties to be considered facilitating a variety of stochastic modeling approaches. Several dedicated two-stage stochastic approaches have been proposed. The capacity configuration decision is typically modeled in the first stage, using MILP-based models to optimize lifecycle performance in the second stage, as seen in Chandra et al. (2005), Francas et al. (2011), and Liu et al. (2015). In their fundamental work, Eppen et al. (1989) suggest a stochastic programming approach integrating the expected downside-risk measure into capacity planning at automotive plants subject to uncertainty.

Dynamic capacity planning is characterized by sequential decision making over the planning horizon and is thus typically captured through multi-stage stochastic programming approaches based on MDP formulations. Most of the existing MDP-based approaches belong to the field of capacity expansion problems, which is reviewed in Van Mieghem (2003). Typically, the demand is modeled as a stochastic process during the lifecycle of one or more products and is tracked in the MDP's state variable. One of the first generic MDP-based capacity planning approaches is due to Bean et al. (1992). Several variations of the generic problem followed, e.g. in Kouvelis and Milner (2002), proposing an approach for capacity expansion considering optional, stochastic outside supply, or in Wang et al. (2013), studying capacity adjustments with technology options defined by uncertain savings based on the former's sustainability.

More industry-specific modeling approaches have been published over the last decade, including two approaches set in an automotive context. Stephan et al. (2010) propose a multi-stage stochastic model for capacity expansion planning taking a commercial truck manufacturer's multi-site network into consideration. The underlying MDP assumes stochastic demand evolution to support capacity expansion over the lifecycles of trucks. Qi et al. (2017) propose a stylized stochastic dynamic program for capacity adjustment during the lifecycle of a single product. They consider new information on demand, which is observed during the lifecycle, by employing Bayesian updating and penalize

capacity changes in order to model managerial hurdles. The numerical study uses the demand and financial data of a selected car model of an American manufacturer.

Kaminsky and Yuen (2014) provide the sole contribution on initial capacity planning projects before SOP. Here, the MDP is used to model the random outcomes of drug trials during a new drug's approval phase, which is part of a capacity planning project in the pharmaceutical industry. It considers new information about drug-trial success over the course of the capacity planning project for the new drug and employs Bayesian updating for the success probabilities. Having a completely different industry focus, many core requirements of capacity planning projects in an automotive context, such as the cyclic forecasting pattern, sequential production process with shared and dedicated stages, and time-phased decision making, remain unconsidered.

Bayesian updating methodology was originally used in inventory theory, as seen in one of the first associated publications in Azoury (1985). However, it has recently been used in dynamic capacity planning (cf. Kaminsky and Yuen, 2014; Qi et al., 2017).

Risk consideration is essential to capacity planning (Eppen et al., 1989). However, this is difficult in dynamic approaches, because traditional risk measures, such as the CVaR, and the resulting decision problems are not necessarily time consistent. Just a few time-consistent risk measures exist. Iyengar (2005) proposes a robust formulation of discrete-time dynamic programming under ambiguity of the transition probabilities. In this so-called maximin approach, the minimum reward of every period is maximized. Boda and Filar (2006) introduce an alternative time-consistent dynamic risk measure called Target Percentile. It minimizes the probability of not achieving a defined target return. Furthermore, Pflug and Pichler (2016) show how the CVaR can be decomposed into a time-consistent formulation. The corresponding MDP is based on the inverse formulation of the CVaR with random probability levels.

Although highly relevant for the industry, academic researchers have not yet studied time-phased decision making in capacity planning projects for new automotive models. Especially the interaction with forecasting processes has been insufficiently researched. Despite its practical relevance, the incorporation of risk into dynamic capacity planning has also remained unaddressed. We aim to contribute to close these gaps.

Our research differs from existing research by focusing on the project character of automotive capacity planning. Thus, the suggested MDP-based dynamic programming approach supports time-phased decision making, considers information updates from the cyclic forecasting process becoming available during the course of the projects, and supports time-phased decision making taking risk attitudes into account.

4.3. Capacity planning projects based on cyclic forecasting

Car manufacturers plan capacities as part of the new product development process of a vehicle model. Every vehicle model has multiple derivatives such as sedan, station wagon and coupé. Derivatives of the same vehicle model are allocated to one or more sites. They can share capacity to a large extent and have SOP within a few years. A capacity-planning unit plans and realizes the capacity for a derivative in a multi-year project terminating with the SOP. We thus focus on capacity planning projects for a set of derivatives, V, of the same vehicle model at a selected site.

Capacity adjustments are avoided during the lifecycles, as they result in longer lead times and lost sales. Instead, operating modes (variations of tact times and shift models) are selected to vary the capacity level based on the installed equipment. We thus assume a separation of the capacity project phase with periods T, during which capacity planners select capacity configurations based on configuration alternatives A, and the lifecycle phase with periods L, during which operating modes are selected periodically based on the suitable modes S.

During a project, a configuration is selected for every stage of the manufacturing process, consisting of the press shop, body shop, paint shop, and final assembly. Here, we distinguish two sets, I and J. All derivatives $v \in V$ share every stage $i \in I$, enabling pooling, whereas every stage $j \in J$ is dedicated to a specific derivative $v \in V$, i.e. $|V|$ parallel lines are used ($J = V$).

Press shop, paint shop, and final assembly are operated as a shared stage, i.e. $I = \{1, 2, 3\}$. In the press shop ($i = 1$) heavy press machinery is used with only derivative-specific dies to shape body parts. In the paint shop ($i = 2$) automated and specialized equipment, which only a few companies supply, is needed to paint the body. In the final assembly ($i = 3$) mostly manual labor and standard equipment are used to assemble a wide range of components to the car.

The body shop typically operates a dedicated line for each derivative ($J = V$), as the assembly of the body-in-white is an automated, derivative-specific process. However, enabled by modularization, manufacturers have recently introduced flexible body shops, which are shared by several derivatives of a vehicle model. The complex process design demands heavy investments. Due to the derivatives' diverse SOPs, this results in a complex trade-off for automotive manufacturers.

These characteristics have two implications for capacity projects. First, differences in
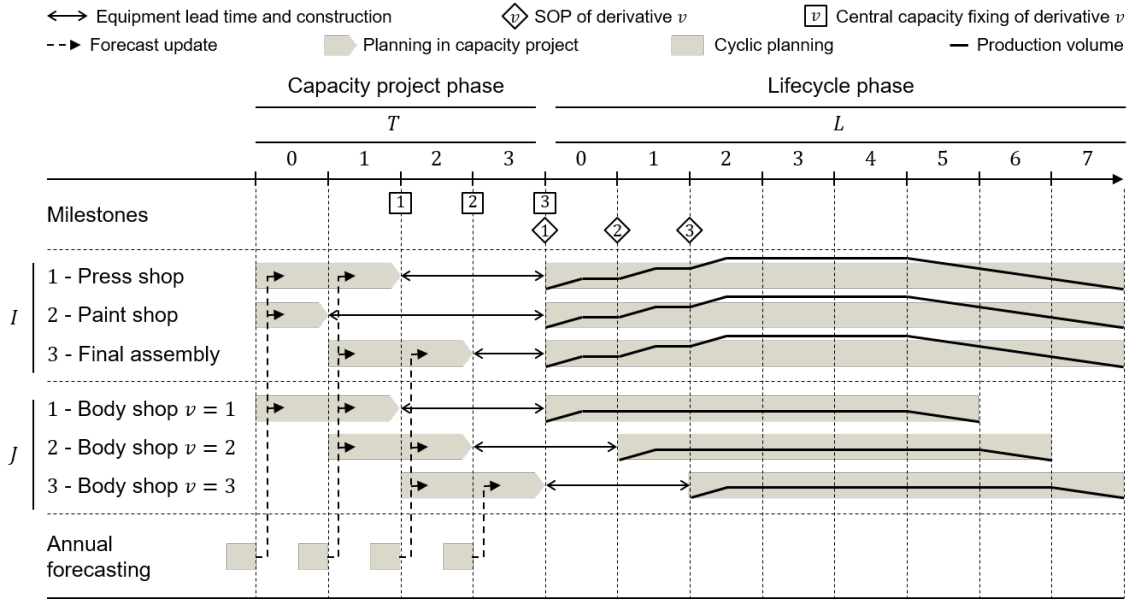
Figure 4.1: Example of time-phased decision making in capacity projects for three derivatives.

manufacturing-system complexity and equipment-supplier markets cause varying construction time and equipment lead time among the manufacturing stages. Thus, the decisions made about their configuration are distributed over the course of a project. For example, high complexity and low supplier density result in three years to design and construct the paint shop, whereas the less complex final assembly needs just one year. Second, pooling on stages $i \in I$ causes the capacity projects to interact. The planning of stages $i \in I$ is aimed at the earliest of the various SOPs. Thus, for all derivatives with later SOP, the planning process is expedited compared to their dedicated stages $j \in J$.

Combined, we refer to this as time-phased decision making with fixing periods F distributed over the capacity project phase $(F = T \setminus \{0\})$ and fixing period of shared (dedicated) stage $i \in I$ ($j \in J$) $f_i^I \in F$ ($f_j^J \in F$). Figure 4.1 illustrates this for the example of three derivatives. The paint shop capacity is already decided three years before the first SOP ($f_2^I = 1$), whereas for the press shop and final assembly, the decisions are made one and two years later ($f_1^I = 2$, $f_3^I = 3$). The capacity for each of the dedicated body shops $j \in J$ is decided two years before the SOP of the associated derivative $v = j$ ($f_1^J = 2$, $f_2^J = 3$, $f_3^J = 4$).

The configuration of each manufacturing stage is based on forecasts of the uncertain demand for the lifecycle derived by a dedicated forecasting unit. Due to the size and organizational structure of automotive manufacturers, the forecasting unit is separated

from the capacity planning unit. The forecasts are updated annually and provided to the capacity planners in the projects (cf. Figure 4.1).

However, the capacity planners' being uninvolved in the forecasting process conduces to a lack of trust and, from the planners' perspective, amplified uncertainty. We thus model the annual updates as a stochastic process based on the discrete random variable d. It is observed before every period $t \in T$ and indicates the forecasting scenario received based on the set of potential demand scenarios D. Several updates are received as the projects progress. Capacity planners can thus use additional information including the past development of the forecasts instead of merely taking the new forecast for granted.

Making time-phased decisions based on uncertain, annually updated forecasts is challenging. The capacity configurations of the different stages are based on different versions of the forecast and can thus be misaligned. Furthermore, demand in the lifecycle can deviate from the forecasts. Consequently, manufacturers must trade off lost sales against overcapacities. The expensive manufacturing equipment therefore occasions high investment risk.

To prevent misalignment, some manufacturers practice central capacity fixing: The capacity configurations of all stages used by a derivative $v \in V$ are centrally fixed simultaneously and subsequent forecast updates are ignored. Figure 4.1 shows the implication for time-phased decision making in the case of central capacity fixing two years before SOP. Due to the central capacity fixing, the final assembly is already fixed in period two, whereas, based on its construction and procurement lead time, the capacity decision would not be required prior to period 3. Decision making is thereby expedited and becomes less flexible.

4.4. Capacity planning projects as Markov decision process

Our approach supports time-phased decision making during the capacity project phase based on cyclic forecasting, as outlined in Section 4.3. It enables flexible decision making over the course of the projects, while limiting the associated investment risk for the manufacturer. Modeling the interdependencies between the time-phased decision making process, the capacity and flexibility levels at the different stages of the automotive manufacturing process, and the operating modes during the lifecycle phase is challenging.

Figure 4.2: Illustration of the CPM-LCM based on example of Figure 4.1.

Figure 4.2 illustrates the approach's structure. It combines two separate models, which represent the two planning phases: (1) capacity planning model (CPM) and (2) lifecycle model (LCM). We refer to the combined approach as CPM-LCM. The CPM models the capacity project phase and is described in detail in this section. All symbols used in the CPM and its adaptions are summarized in Appendix A.1. The LCM, on the other hand, anticipates tactical planning over the lifecycle phase. A MILP determines the operating modes and production volumes for each production stage and period aiming to maximize NPV. An operating mode is defined by a shift model and tact time. Similar to previous approaches (e.g. Bihlmaier et al., 2009), the LCM specifies annual capacity based on the installed technical capacity configuration. Details on the LCM can be found in Appendix A.2.

4.4.1. Modeling time-phased decision making in the capacity planning phase

Due to its ability to model sequential decision making, the MDP is selected as basis of the CPM. It is well suited to capturing the dynamic character of time-phased decision

making and the interactions with cyclic forecasting; however, it comes with the limitation of specified, known forecasting scenarios, i.e. set D is assumed to be known to the capacity planners.

The CPM is defined as a finite $|T|$-horizon MDP with action a_t and multi-dimensional state s_t. Action a_t describes the selection of a capacity configuration from the discrete set of configuration alternatives A in every capacity planning period t based on the current state s_t. If a shared manufacturing stage i (dedicated stage j) has its fixing period f_i^I (f_j^J) in $t+1$, action a_t triggers investment costs $\lambda_i^I(a_t)$ ($\lambda_j^J(a_t)$). Note that action a_t applies to all manufacturing stages i (j) with fixing period $f_i^I(f_j^J) = t+1$, i.e. these stages have the same capacity configuration. This resembles industry practice, as capacity planners base all decisions in a period on the same forecast scenario.

State $s_t = (c_t, d_t, n_t)$ tracks the information available to the capacity planner before action a_t is taken. It contains information on the capacity configurations fixed, c_t, as result of the time-phased decision making and on the annual forecasting process, i.e. the latest demand forecast d_t and the forecast history n_t.

Vector $c_t = (c_{tf})_{f \in F}$ is the central modeling component enabling time-phased decision making. State variables $(c_{tf})_{f \in F}$ indicate the capacity configuration selected for all production stages fixed in period f. c_{tf} resembles a_{t-1} for $f \geq t$ and stays constant, i.e. resembles $c_{t-1,f}$, for $f < t$ to represent the equipment lead time and construction time. The MDP thus becomes partially controllable.

To implement this behavior, we define the partial state transition, $\rho(c_{t+1}|c_t, a_t)$, as follows:

Definition 4.1. *For time-phased decision making in capacity planning projects, the partial state transition from c_t into c_{t+1} due to action a_t is defined as*

$$\rho_t(c_{t+1}|c_t, a_t) = \begin{cases} 1 & \text{if } c_{t+1,f} = a_t \ \forall f > t \quad \wedge \quad c_{t+1,f} = c_{tf} \ \forall f \leq t \\ 0 & \text{otherwise.} \end{cases} \tag{4.1}$$

Figure 4.2 shows an example to demonstrate this principle. We use the example introduced in Figure 4.1 with $V = \{1, 2, 3\}$. Furthermore, we assume a set of three alternative configurations $A = \{1, 2, 3\}$. In period $t = 0$, the CPM is initialized with s_0. Capacity configuration $a_0 = 2$ is selected based on s_0. As this is not a fixing period, state vector elements are transitioned into $(c_{1f})_{f \in F} = a_0 = 2$ for the next period. In period $t = 1$, capacity configuration $a_1 = 3$ is chosen based on s_1. As the first fixing period, $f = 1$, is reached, only the state vector elements $(c_{2f})_{f \in \{2,3,4\}}$ adopt the selected

capacity configuration a_1. State vector element c_{21} stays unchanged (indicated by the dotted box), i.e. equal to a_0, and sets the configuration for all stages i (j) with fixing period $f_i^I(f_j^J) = 1$, in our example the capacity of the paint shop ($i = 2$) is set to level 2. In period $t = 2$, the configuration is revised and changed to $a_2 = 2$, leading to a transition into $(c_{3f})_{f \in \{3,4\}} = a_2 = 2$ and $(c_{3f})_{f \in \{1,2\}} = (c_{2f})_{f \in \{1,2\}}$, i.e. $c_{31} = a_0 = 2$ and $c_{32} = a_1 = 3$, as configurations of stages i (j) with fixing periods $f_i^I(f_j^J) = 1$, i.e. the paint shop ($i = 2$), and $f_i^I(f_j^J) = 2$, i.e. the press shop ($i = 1$) and the body shop $j = 1$, cannot be adapted anymore. The same logic is applied until termination period $t = 4$ is reached and all stages have been fixed. Based on c_4, the LCM is initialized with annual capacity levels ζ_{ias}^I and ζ_{jas}^J for the shared and dedicated stages. The actual capacity is determined by the operating modes $s \in S$ selected in the LCM.

Furthermore, state variable d_t indicates the latest demand forecast provided by the forecasting unit before period t, i.e. the latest realization of the discrete random variable d. As the capacity planners are uninvolved in the forecasting process (cf. Section 4.3), they have no knowledge about the distribution of the forecasting scenarios. However, instead of assuming a random walk for d_t, we consider information about the forecasting history collected by the capacity planners during the capacity project phase to capture the anticipation of future forecasts. Thus, the capacity planners update their beliefs about the probability distribution of future forecasting updates based on the forecasts observed up to period t. Bayesian updating is therefore employed for the forecasting scenario probabilities assuming an unknown probability π_d for scenario d, with $\pi_d \in [0,1]$ and $\sum_{d \in D} \pi_d = 1$.

To employ Bayesian updating for the forecasting scenario probabilities in the model, the state variable vector $\boldsymbol{n}_t = (n_{td})_{d \in D}$ is defined to track the forecasting history. State variable $(n_{td})_{d \in D}$ counts the number of observations of forecasting scenario d up to period t (including the latest forecast d_t), which is assumed to be a Bernoulli event with Bayesian estimate $\bar{\boldsymbol{\pi}}_t = (\bar{\pi}_{td})_{d \in D}$. For details on the derivation of $\bar{\boldsymbol{\pi}}_t$ we refer to Appendix A.3.

To implement the Bayesian updating in the CPM, we define partial state transitions, $\pi_t(d_{t+1}|\boldsymbol{n}_t)$ and $\sigma_t(\boldsymbol{n}_{t+1}|\boldsymbol{n}_t, d_{t+1})$, as follows:

Definition 4.2. *For cyclic forecasting updates in capacity planning projects, the partial state transitions from d_t and $\boldsymbol{n}_t$ to d_{t+1} and $\boldsymbol{n}_{t+1}$ are defined by*

1. *the stochastic transition probability* $\pi_t(d_{t+1}|\boldsymbol{n}_t)$,

$$\pi_t(d_{t+1}|\boldsymbol{n}_t) = \bar{\pi}_{td} = \frac{\alpha_d + n_{td}}{\sum_{d' \in D}(\alpha_{d'} + n_{td'})}, \; and \tag{4.2}$$

2. *the controllable transition* $\sigma_t(\boldsymbol{n}_{t+1}|\boldsymbol{n}_t, d_{t+1})$,

$$\sigma_t(\boldsymbol{n}_{t+1}|\boldsymbol{n}_t, d_{t+1}) = \begin{cases} 1 & \text{if } n_{t+1,d} = n_{td} + 1, d = d_{t+1} \; \wedge \; n_{t+1,d'} = n_{td'}, d' \neq d_{t+1} \\ 0 & \text{otherwise.} \end{cases} \tag{4.3}$$

The principle of Bayesian updating employed in the CPM is illustrated in Figure 4.2. In accordance with set A, we assume a set of three forecasting scenarios $D = \{1, 2, 3\}$. As no prior information apart from the first forecast is available before period 0, we use $\alpha_d = 1 \; \forall d \in D$. With the first forecast being $d_0 = 2$, the forecasting history vector is initialized as $\boldsymbol{n}_0 = (0, 1, 0)$. The probability of forecasting scenario d_1 in the next period is then computed as Bayesian estimate $\bar{\boldsymbol{\pi}}_0$, resulting in the probabilities $\bar{\pi}_{01} = \bar{\pi}_{03} = 0.25$ and $\bar{\pi}_{02} = 0.5$. After observing the forecast $d_1 = 3$, Bayesian updating is applied based on the vector $\boldsymbol{n}_1 = (0, 1, 1)$ resulting in new probabilities $\bar{\pi}_{11} = 0.2$ and $\bar{\pi}_{12} = \bar{\pi}_{13} = 0.4$. The same logic is applied for the CPM's remaining periods.

Based on the defined partial state transitions and on initial state $\boldsymbol{s}_0 = (\boldsymbol{c}_0, d_0, \boldsymbol{n}_0)$, the value function is formulated as a dynamic program implementing the finite $|T|$-horizon MDP of the CPM as follows:

$$V_t(\boldsymbol{s}_t) = \max_{a_t \in A} \left\{ -\sum_{i \in I} \theta_{it}^I \lambda_i^I(a_t) - \sum_{j \in J} \theta_{jt}^J \lambda_j^J(a_t) + \beta E_{\rho_t, \pi_t, \sigma_t}[V_{t+1}(\boldsymbol{s}_{t+1})] \right\} \tag{4.4}$$

with terminal value function $V_{|T|}(\boldsymbol{s}_{|T|}) = NPV^{LCM}(\boldsymbol{s}_{|T|})$.

In Equation (4.4), the NPV is maximized assuming optimal behavior in period $t + 1$. θ_{it}^I and θ_{jt}^J are binary parameters modeling the fixing period for shared stage i and dedicated stage j. θ_{it}^I (θ_{jt}^J) assumes a value of 1, if shared stage i (dedicated stage j) has fixing period f_i^I (f_j^J) $= t + 1$, and a value of 0 otherwise. Furthermore, $\beta \in [0, 1]$ is the discounting factor and $E_{\rho_t, \pi_t, \sigma_t}[...]$ is the expected value with respect to the partial transitions ρ_t, π_t, and σ_t as defined in Equations (4.1), (4.2), and (4.3). Finally, $NPV^{LCM}(\boldsymbol{s}_{|T|})$ is the optimized NPV resulting from the LCM initiated with termination state $\boldsymbol{s}_{|T|}$, i.e. assuming technical capacity configuration $\boldsymbol{c}_{|T|}$ and demand according to forecasting scenario $d_{|T|}$ for the lifecycle phase (cf. Figure 4.2).

4.4.2. Modeling risks in time-phased decision making based on the conditional value at risk

In the previous sections, we assumed risk-neutral capacity planners maximizing the expected NPV. However, as described in Section 4.3, capacity planning projects in the automotive industry are subject to great investment risk. We thus present a model extension capturing risk attitudes in time-phased capacity planning. As we are focusing on modeling capacity planning projects, a suitable risk measure is implemented for the project phase, resulting in an extended, risk-averse version of the CPM denoted as capacity planning model considering risk (CPMR).

The most popular risk measure in stochastic risk-averse optimization is the CVaR. However, employing the CVaR in a dynamic context results in a time-inconsistent decision problem. A stochastic multi-stage decision problem is time-consistent, if the original decision in an early stage remains optimal after observing some random outcomes. We hence make use of the decomposition theorem defined by Pflug and Pichler (2016). In the following, we give a brief outline of the decomposition theorem. More details can be found in Appendix A.4.

We formulate the CPMR as a dynamic program maximizing the CVaR in period $t = 0$ with probability level γ for the uncertain NPV of a capacity project, i.e. the conditional NPV for only the γ lowest NPV realizations.

Figure 4.3 illustrates the consequences of time-inconsistency of the CVaR and the principle of the CVaR decomposition theorem. It is based on a simplified example of a capacity project with duration $|T| = 2$. The probabilities of forecasting scenarios $D = \{1, 2\}$ change over the stages due to Bayesian updating. Note that the tree is based on selected capacity configurations $a_0 = 1$ and $a_1 = 1$ or 2. In the following, we apply a CVaR level of $\gamma = \frac{1}{3}$. No discounting is applied, i.e. $\beta = 1$.

When calculating the CVaR with a constant level $\gamma = \frac{1}{3}$ throughout the multi-stage setting, we first calculate the CVaR for the upper and lower sub-tree. We obtain a CVaR of 1 and of $\left(\frac{1}{4} \times \frac{1}{2} + \left(\frac{1}{3} - \frac{1}{4}\right) \times 2\right) \times 3 = \frac{7}{8}$, respectively. At the root only the lower sub-tree needs to be considered, because of its probability of $\frac{2}{3}$, resulting in a CVaR of $\frac{7}{8}$ in period $t = 0$. However, the value of the CVaR obtained by considering each branch over the entire horizon separately equals $\frac{3}{4}$. The reason for the difference is that instead of the case with the low NPV of 1 in the upper sub-tree the case with the high NPV of 2 in the lower sub-tree is considered.

To capture the contribution of each sub-tree to the CVaR, the decomposition theorem
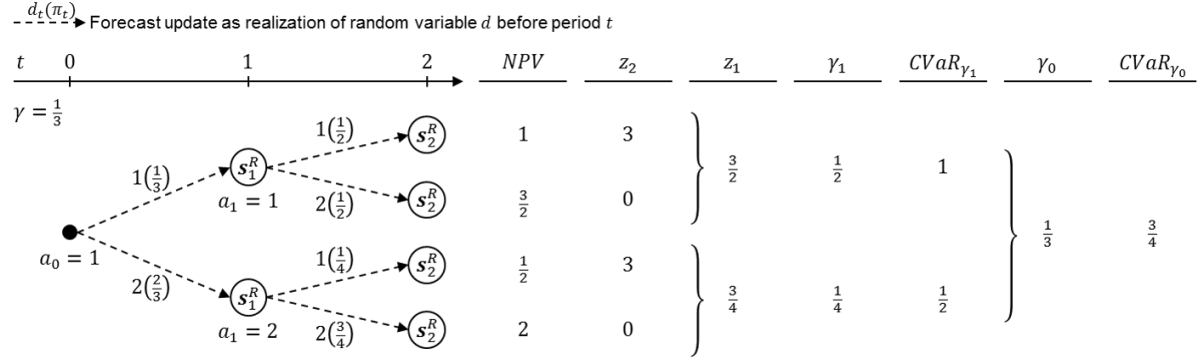
Figure 4.3: Illustration of the CVaR decomposition theorem based on simplified example.

applies a variable CVaR level $\gamma_t \in [0,1]$. It depends on the realization of the random demand forecasts up to t, i.e. on the path taken in the underlying probability tree. Note that demand forecast d_t is random from the perspective of all periods $t' < t$ and therefore γ_t is random, too.

Hence, in accordance with the decomposition theorem, we use the dual representation of the CVaR, which is based on densities z_t. For every future state of the multi-stage situation, the density equals the expectation of the future period's densities given the path taken up to the current state. They determine the weight of the CVaR contribution for each node and cannot exceed $\frac{1}{\gamma_t}$ (cf. the Appendix A.4 for more details). In the example for the CVaR with $\gamma = \frac{1}{3}$ of Figure 4.3, we hence initialize densities z_2 by assigning a value of 3 to the two scenarios that contribute to the CVaR. The values of z_1 are then calculated as expected value of z_2 using the information available in period $t = 1$.

The CVaR in any period t with level γ_t can then be decomposed based on the densities and the variable CVaR level. It corresponds to the expectation of the product of densities z_τ, $\tau > t$, and values of the CVaR with level $\gamma_\tau = \gamma_t z_\tau$. For the upper sub-tree in our example, we first determine $\gamma_1 = \gamma_0 \times z_1 = \frac{1}{3} \times \frac{3}{2} = \frac{1}{2}$. The CVaR for $t = 1$ is then calculated for level $\gamma_1 = \frac{1}{2}$, in our case being equal to 1. Using z_1 and the CVaR with level γ_1 of both sub-trees, we can compute the CVaR in period $t = 0$ as expectation of the product of z_1 and the values of the CVaR with level γ_1, i.e. $\frac{1}{3} \times \frac{3}{2} \times 1 + \frac{2}{3} \times \frac{3}{4} \times \frac{1}{2} = \frac{3}{4}$.

To adapt the CVaR decomposition for implementation in the multi-period dynamic program, concepts for the representation of variable γ_t, the determination of densities z_t, and the maximization of the CVaR based on the selection of capacity configurations a_t have to be developed.

To track the random CVaR level γ_t, a dedicated state variable is required for the

MDP. Therefore, the continuous γ_t is discretized as follows: The domain $[0, 1]$ is divided into $|R|$ intervals leading to the set of probability level intervals $R = \{1, 2, ..., |R|\}$ with borders $\big((r - 1)\hat{\gamma}, r\hat{\gamma}\big]$ and $\hat{\gamma} = \frac{1}{|R|}$. Furthermore, we introduce the state variable $r_t \in R$ to track the probability level interval of period t. We refer to the extended state as $\boldsymbol{s}_t^R = (\boldsymbol{c}_t, d_t, \boldsymbol{n}_t, r_t)$.

To adapt $\gamma_\tau = \gamma_t z_\tau$ for the discrete setting, the additional partial state transition, $\varphi_t\big(r_{t+1}|r_t, z_{t+1}(d_{t+1})\big)$, is introduced using the densities z_t:

Definition 4.3. *For risk-averse time-phased decision making in capacity planning projects based on the CVaR, the partial state transition from r_t into r_{t+1} due to densities $z_{t+1}(d_{t+1})$ is defined as*

$$\varphi_t\big(r_{t+1}|r_t, z_{t+1}(d_{t+1})\big) = \begin{cases} 1 & \text{if } r_t \; \hat{\gamma} \; z_{t+1}(d_{t+1}) \in \big((r_{t+1} - 1)\hat{\gamma}, r_{t+1}\hat{\gamma}\big] \\ 0 & \text{otherwise.} \end{cases} \tag{4.5}$$

We determine the densities z_t separately for each stage and action of the finite $|T|$-horizon MDP by solving the following minimization problem, which uses the densities as decision variables:

$$v_t^R(\boldsymbol{s}_t^R, a_t) = \min_{z_{t+1} \geq 0} E_{\rho_t, \pi_t, \sigma_t, \varphi_t}[z_{t+1}(d_{t+1}) \; V_{t+1}^R(\boldsymbol{s}_{t+1}^R)] \tag{4.6}$$

$$E_{\pi_t}[z_{t+1}(d_{t+1})] = 1 \tag{4.7}$$

$$z_{t+1}(d_{t+1}) \leq \frac{1}{r_t\hat{\gamma}} \quad \forall d_{t+1} \in D \tag{4.8}$$

with terminal value function $V_{|T|}^R(\boldsymbol{s}_{|T|}^R) = NPV^{LCM}(\boldsymbol{s}_{|T|}^R)$.

In Equation (4.6), the expectation of the product of $V_{t+1}^R(\boldsymbol{s}_{t+1}^R)$, i.e. the maximized CVaR in period $t + 1$ with discretized probability level, and $z_{t+1}(d_{t+1})$, i.e. the densities of forecasting scenarios d_{t+1}, is minimized assuming the transition parameters defined in Equations (4.1), (4.2), (4.3) and (4.5). Equations (4.7) and (4.8) are necessary to ensure the density properties for $z_{t+1}(d_{t+1})$ required for the decomposition theorem. Note that the minimization problem is non-linear due to the dependency of the state transition φ_t used in Equation (4.6) on decision variable z_{t+1}.

Finally, based on the optimal solutions of Equation (4.6), we determine the CVaR-
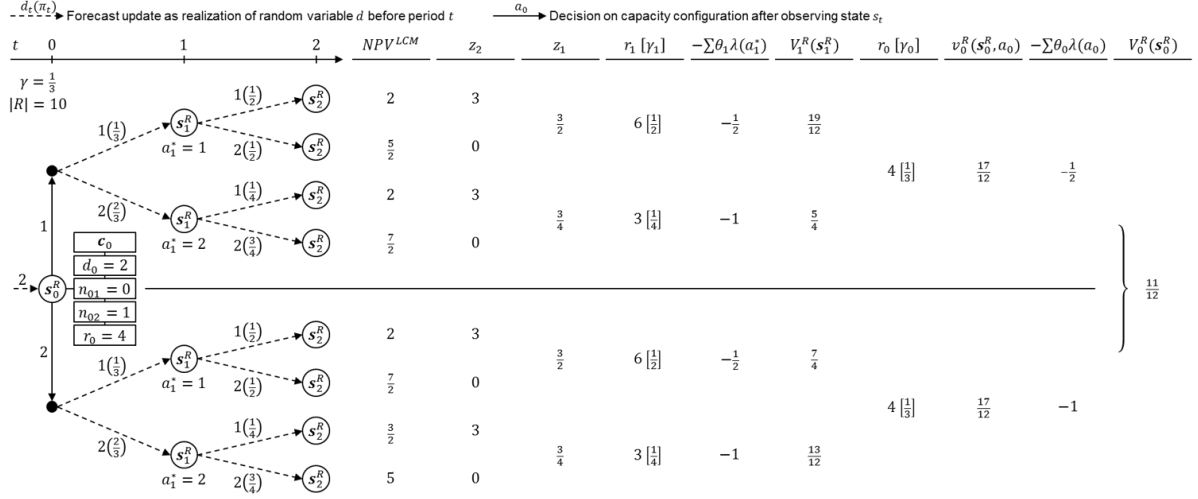
Figure 4.4: Illustration of the CPMR based on simplified example.

maximizing capacity configuration by solving the following finite $|T|$-horizon MDP:

$$V_t^R(\boldsymbol{s}_t^R) = \max_{a_t \in A} \left\{ - \sum_{i \in I} \theta_{it}^I \lambda_i^I(a_t) - \sum_{j \in J} \theta_{jt}^J \lambda_j^J(a_t) + \beta v_t^R(\boldsymbol{s}_t^R, a_t) \right\}. \qquad (4.9)$$

The optimal action in period 0 is derived based on the Bellman principle and initial state $\boldsymbol{s}_0 = (\boldsymbol{c}_0, d_0, \boldsymbol{n}_0, r_0)$. Hence, to implement the decomposition theorem and maximize the CVaR in the CPMR, we split the value function into an inner minimization, represented by Equations (4.6) to (4.8), and an outer maximization, represented by Equation (4.9) (Gönsch et al., 2018).

Figure 4.4 illustrates the CPMR. It is based on the simplified example of Figure 4.3. The decision maker chooses capacity levels $a_t \in \{1, 2\}$ triggering investment costs of $\sum \theta_t \lambda(a_t) \in \{\frac{1}{2}, 1\}$ (note that for simplicity we omit indices i and j). Here we see the iteration in period $t = 0$.

We can observe the concept implemented in the CPMR to represent the variable level γ_t. We use $|R| = 10$ intervals to discretize γ_t, i.e. $\hat{\gamma} = 0.1$. Based on $\gamma = \gamma_0 = \frac{1}{3} \in (0.3, 0.4]$, r_0 assumes a value of 4. The transition into state r_1 for each sub-tree is then conducted applying function φ_0. For the upper sub-tree, for example, $\varphi_0(6|4, \frac{3}{2}) = 1$, as $r_0 \times \hat{\gamma} \times z_1 \in (0.5, 0.6]$. The value in square brackets represents the original value of γ_t (cf. Figure 4.3) and indicates potential inaccuracies due to the discretization, e.g. in the upper sub-tree a level of 0.5 would be applied in the continuous case instead of the level of 0.6 used in the CPMR.

Furthermore, the concepts of the inner minimization to determine densities z_t and

of the outer maximization to derive the CVaR maximizing capacity configuration are illustrated. For each capacity configuration $a_0 \in \{1, 2\}$, the value v_0^R and the densities $z_1(d_1)$ are shown, both determined by solving the inner minimization problem of Equations (4.6) to (4.8) using function φ_0 for the state transition and values V_1^R. For action $a_0 = 1$, for example, v_0^R assumes a value of $\frac{1}{3} \times \frac{3}{2} \times \frac{19}{12} + \frac{2}{3} \times \frac{3}{4} \times \frac{5}{4} = \frac{17}{12}$, where the optimal values of $z_1(1)$ and $z_1(2)$ are $\frac{3}{2}$ and $\frac{3}{4}$. The V_1^R values have been derived during the backwards iteration by determining the capacity configuration a_1^* that maximizes the CVaR of the NPV^{LCM} and investment costs $\sum \theta_1 \lambda(a_1)$ based on state $\boldsymbol{s}_1^R$ with a level according to r_1. In the upper sub-tree, for example, based on state variable $r_1 = 6$ a level of $\frac{6}{10}$ is applied for the CVaR maximization, resulting in optimal action $a_1^* = 1$ and $V_1^R = \left(\frac{1}{2} \times 2 + \frac{1}{10} \times \frac{5}{2}\right) \times \frac{10}{6} - \frac{1}{2} = \frac{25}{12} - \frac{1}{2} = \frac{19}{12}$, where $-\frac{1}{2}$ results from the investment triggered by capacity configuration $a_1^* = 1$.

Based on v_0^R of alternative configurations 1 and 2, the CVaR-outer-maximizing action $a_0^* = 1$ is derived, as $V_0^R = \max\{-\frac{1}{2} + \frac{17}{12}, -1 + \frac{17}{12}\} = \frac{11}{12}$. (Note that the values show a different split from the values in Figure 4.3, as we treat investment cost separately for each node in accordance with the CPMR Equations (4.6) and (4.9).)

4.5. Numerical analysis

In this section we present a detailed analysis of time-phased decision making in capacity projects. Based on the results of several numerical experiments, we compare our approach to the state-of-the-art in academic literature and industry practice and discuss managerial insights into the following questions:

1. What value does the CPM(R)-LCM have for time-phased decision making in capacity projects?

2. What impact does central capacity fixing have during capacity projects?

3. What impact does the increased process flexibility enabled by modularization on time-phased decision making have in capacity projects?

4.5.1. Implementation, design of experiments, and computational performance

Sanitized information obtained during interviews at a manufacturer was combined with data publicly available from annual reports and Ph.D. dissertations written in collabo-
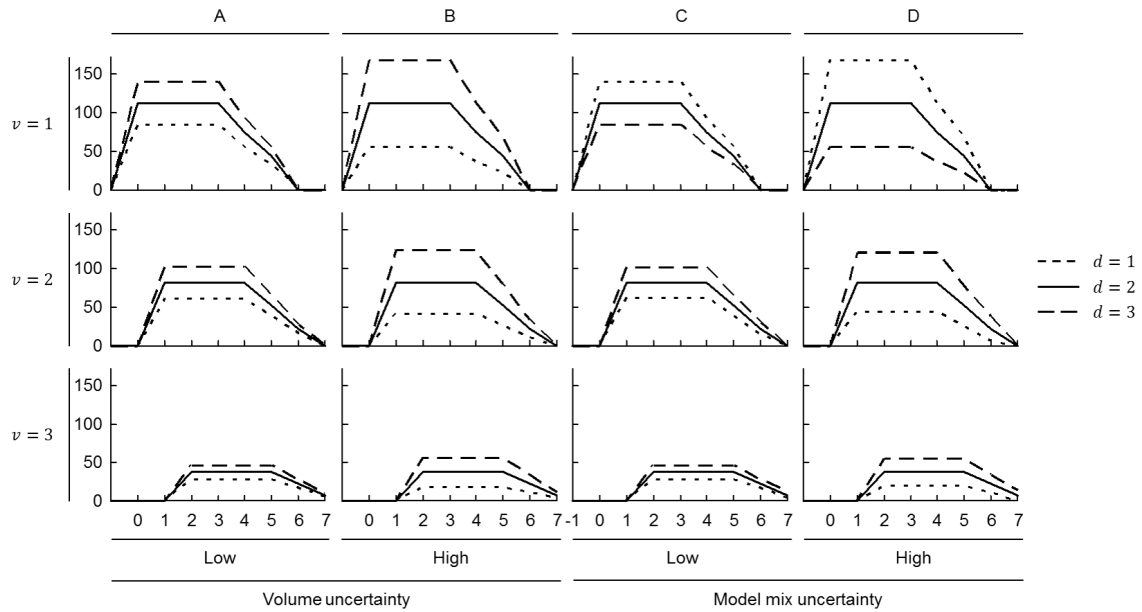
Figure 4.5: Overview of the investigated parameter settings for the demand forecast.

ration with automotive manufacturers (see Volling et al., 2013) to generate the data.

We consider a typical new vehicle introduction consisting of three new derivatives $V = \{1, 2, 3\}$, e.g. sedan, station wagon and coupé, with SOPs in periods $l = 0, 1, 2$, resulting in a capacity project phase with a duration of $|T| = 4$ years, and capacity fixing for the shared stages $I = \{1, 2, 3\}$, i.e. press shop, paint shop, and final assembly, and the dedicated body shops $J = V$ as illustrated in Figure 4.1. The derivatives are characterized by different volume and profitability levels, i.e. a base derivative with high volume and low profitability ($v = 1$) and two upscale derivatives with low volume and high profitability ($v = 2, 3$). The cyclic forecasting process is represented by three forecasting scenarios, $D = \{1, 2, 3\}$, as often seen in practice. Accordingly, the capacity configuration is chosen from set $A = \{1, 2, 3\}$ with alternatives sorted from lowest to highest annual capacity. The installed capacity configuration can be operated in six modes resembling the shift models seen in the automotive industry, e.g. two or three daily shifts with five or six working days per week. A probability level of $\gamma = 20\%$ was selected for the CVaR.

We analyzed the questions stated above for a variety of the basic data's parameter settings. To analyze the demand uncertainty effects relevant in automotive manufacturing the demand volumes associated with forecasting scenario $d \in D$ were varied as shown in Figure 4.5. Volume uncertainty is represented by settings A and B. Demand volume varies by $\pm 25\%$ and by $\pm 50\%$ for all derivatives, which resembles a low level and a high

level of volatility in the overall market volume. Model mix uncertainty is represented by setting C and D. Demand volume is shifted by 25% and 50% between the base derivative $v = 1$ (market development toward low-end products) and the upscale derivatives $v \in \{2, 3\}$ (market development toward high-end products), which resembles a low level and a high level of volatility in the market's model mix. Other sensitive parameters are the investment costs for body shops as well as the associated production costs and workforce requirements for the operating modes in the LCM, which were considered at levels of $\pm 30\%$ of the base values. We applied a full-factorial design, which results in a total of 108 instances, denoted in the following as set G.

We implemented the CPM-LCM and the CPMR-LCM in C#. For implementation purposes, we used binary dummy variables to model the discrete action a_t. In the CPMR-LCM we linearized the inner minimization problem in Equation (4.6) to (4.8) and introduced according binary variables. The CVaR probability level was discretized using $|R| = 10$ intervals. We observed a solution time of less than three minutes for the CPM-LCM and less than 11 hours for the CPMR-LCM on an Intel Core i5 4200-M with 2.5 GHz and 128 GB RAM using the solver CPLEX v12.5.

4.5.2. Value of multi-stage capacity planning

To answer question 1, in accordance with earlier studies (cf. Huang and Ahmed, 2009), we define the value of the CPM(R)-LCM, ω (ω^R), for risk-neutral (risk-averse), time-phased decision making in capacity planning projects as

$$\omega = \frac{NPV^{CPM} - NPV^B}{NPV^B} \ 100 \ [\%], \quad \omega^R = \frac{CVaR^{CPMR} - VCaR^{BR}}{CVaR^{BR}} \ 100 \ [\%]. \quad (4.10)$$

NPV^{CPM} and $CVaR^{CPMR}$ are determined by the CPM(R)-LCM and NPV^B and $CVaR^{BR}$ are determined by a risk-neutral benchmark model (B) or a risk-averse benchmark model (BR). To compare $CVaR^{CPMR}$ and $CVaR^{BR}$ despite the CPMR-LCM's discretized state space, we performed a post-optimization processing step and recomputed the value of $CVaR^{CPMR}$ based on the configuration determined by the CPMR-LCM applying the nested CVaR formulation.

The benchmark models are based on the current state-of-the-art in academic automotive capacity planning. We use two-stage stochastic programming to model the decision making in the capacity project phase maximizing the NPV for the risk-neutral case, referred to as risk-neutral two-stage stochastic programming with recourse (2SP),
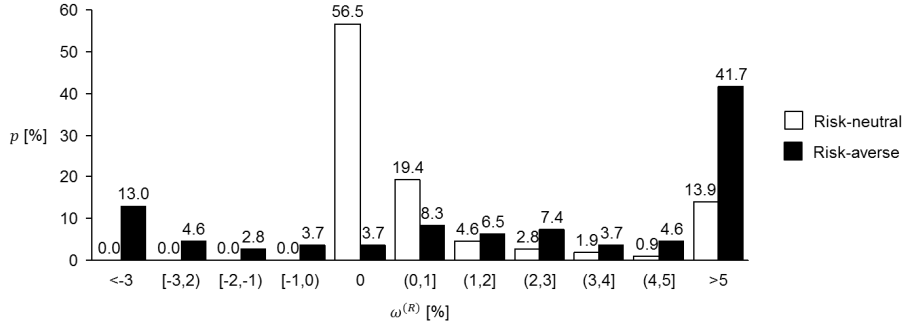
Figure 4.6: Distribution of $\omega^{(R)}$.

and maximizing the CVaR for the risk-averse case, referred to as risk-averse two-stage stochastic programming with recourse (2SPR). Both models are applied in a rolling horizon scheme during the capacity planning phase employing Bayesian updating. The capacity configuration of production stages fixed in the current period t^* of the rolling horizon scheme is the first stage decision, while configurations of stages with fixing later than t^* and all lifecycle decisions are second stage decision. The benchmark models were implemented in C# and solved on the same machine using the solver CPLEX v12.5. Details on both models can be found in Appendix A.5.

In the following, $p(...)$ refers to the relative frequency in the overall population G. Figure 4.6 shows that $p(\omega < 0\%)$ equals 0%. The CPM-LCM thus dominates the 2SP and even strictly dominates it for 43.5% of the instances. Proposition 4.1 extends this finding into a general statement. The proof can be found in Appendix A.6.

Proposition 4.1. *The value of the CPM-LCM for risk-neutral, time-phased decision making in capacity planning projects, ω, is always greater or equal to 0.*

Furthermore, our results for the risk-neutral case indicate a broad range of ω with spikes at the lower tail, $p(\omega \leq 1\%)$ equals 75.9%, and at the upper tail, $p(\omega > 5\%)$ exceeds 13%. For the risk-averse case, the distribution of ω^R shows a strong spike at the upper tail. With $p(\omega^R > 5\%)$ equal to 41.7%, we observe a stronger upside potential for ω^R than for ω. Instances with $\omega^R < 0$ are observable at the lower end. We note that this results from inaccuracies caused by the discretization in the CPMR-LCM.

Observation 4.1. *The CPM-LCM and the CPMR-LCM for risk-neutral and risk-averse, time-phased decision making in capacity planning projects have a significant upside potential compared to conventional approaches.*
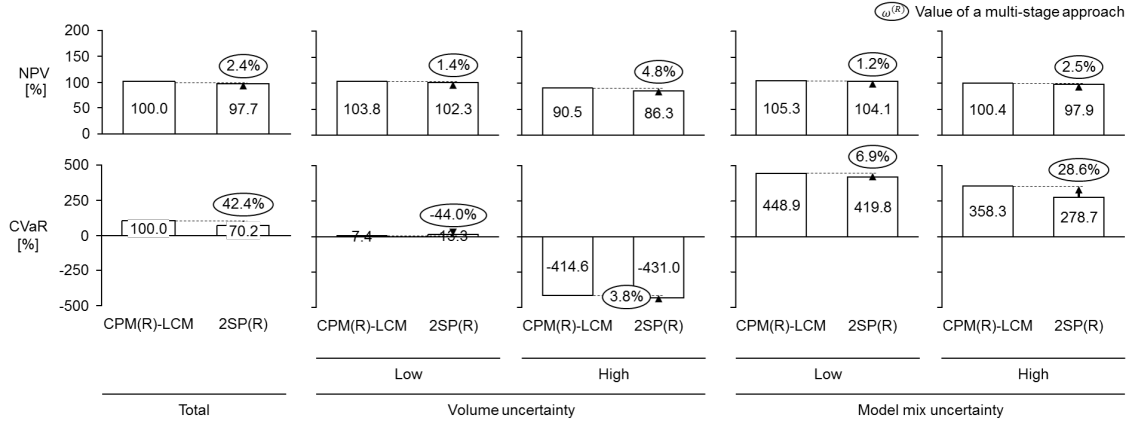
Figure 4.7: Overview of the results for CPM(R)-LCM and 2SP(R).

The total average value of $\omega^{(R)}$ differs significantly between the CPM(R)-LCM applying the two risk attitudes. Figure 4.7 shows that ω^R, having a value of 42.4%, exceeds ω by far, which has a value of 2.4%.

Observation 4.2. *A multi-stage approach is especially valuable for risk-averse, time-phased decision making in capacity planning projects.*

Furthermore, we observe a significant impact of uncertainty. The performance level (NPV and CVaR) drops for both cases of high uncertainty (volume and model mix), as it would be expected. However, both ω and ω^R increase given a high uncertainty level. Thus, reduction of the NPV or CVaR due to the increased uncertainty is reduced by the CPM(R)-LCM when compared with the benchmark model.

Observation 4.3. *The CPM(R)-LCM is especially valuable for time-phased decision making in capacity planning projects in environments subject to elevated uncertainty.*

We note that in our experiments, ω^R turns negative given low volume uncertainty. This again results from discretization in the CPMR-LCM. The large absolute value of ω^R is caused by the very low $CVaR^{BR}$ level of 13.3%, which determines the denominator when calculating ω^R (see Equation (4.10)).

We are furthermore interested in the approach's impact on the alignment between manufacturing stages in time-phased decision making with updated forecasts. We therefore compare the deviation from the average configuration for each stage: For every instance $g \in G$, we compute the average configuration of all stages $\bar{a}_g$. Moreover, we compute $\hat{a}_g = \frac{1}{|I|+|J|} \sum_{i \in I/j \in J} |a_{i/j} - \bar{a}_g|$, i.e. the average deviation from $\bar{a}_g$ across stages

Table 4.1: Overview of results for the CPM(R)-LCM and the 2SP(R).

Model	NPV, CVaR	$\bar{a}$	$\hat{a}$
CPM-LCM	100.0%	2.47	0.28
2SP	97.7%	2.78	0.22
CPMR-LCM	100.0%	2.37	0.30
2SPR	70.2%	2.25	0.34

in instance g. Based on $\hat{a}_g$ and $\bar{a}_g$, we determine the total average configuration $\bar{a}$ and the total average deviation $\hat{a}$ of all 108 instances. Table 4.1 shows the results.

Two effects are observable. First, the risk-averse approaches show a more conservative behavior: $\bar{a}$ is smaller for the CPMR-LCM and 2SPR than for the CPM-LCM and 2SP. Second, risk-aversion in time-phased decision making shows more deviation, meaning that stages are less aligned. Thus, decision making flexibility becomes more important during the capacity planning project. The CPMR-LCM is better suited for such a setting. Having less deviation, it achieves a greater objective value than the 2SPR.

Observation 4.4. *The importance of decision flexibility during time-phased decision making in capacity planning projects increases under risk-aversion.*

4.5.3. Impact of central capacity fixing

Recall the central capacity fixing practiced by automotive manufacturers as described in Section 4.3. To answer question 2, we define the costs of central capacity fixing, μ (μ^R), for risk-neutral (risk-averse), time-phased decision making in capacity planning projects as

$$\mu = \frac{NPV^{NCF} - NPV^{CF}}{NPV^{CF}} \, 100 \; [\%], \quad \mu^R = \frac{CVaR^{NCF} - CVaR^{CF}}{CVaR^{CF}} \, 100 \; [\%]. \quad (4.11)$$

NPV^{NCF} and $CVaR^{NCF}$ result from the CPM(R)-LCM applying no central capacity fixing (NCF); NPV^{CF} and $CVaR^{CF}$ refer to the result of the CPM(R)-LCM with adjusted fixing periods to implement central capacity fixing (CF). In accordance with the industrial practice, we assume central fixing of two periods before the relevant SOP for the CF strategy.

The NCF and CF strategies are compared in Figure 4.8. For the CF strategy, we adjust the setting of parameters θ_{it}^I (θ_{jt}^J) accordingly; however, we use the same discounting periods as those in the NCF, since the investments are still made during the original
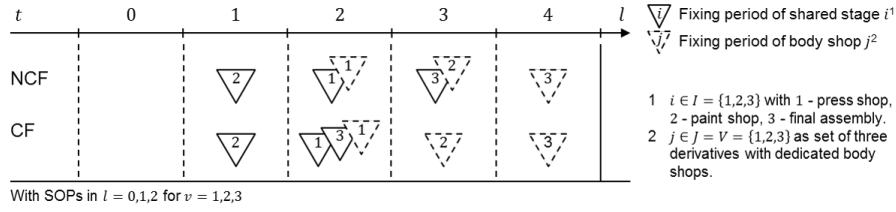
Figure 4.8: Illustration of the NCF and the CF strategy.

fixing period, although the configuration is fixed earlier.

Table 4.2 summarizes the experiment's results. We observe an average μ of 0.4% for a risk-neutral manufacturer. The manufacturer's average costs are thus about 0.4% of the NPV if capacities are centrally fixed earlier to prevent misalignments. We observe higher costs of central capacity fixing for risk-averse manufacturer: μ^R amounts to 2.1%.

Observation 4.5. *Central capacity fixing for time-phased decision making in capacity planning projects comes at the cost of reduced decision flexibility. The loss of decision flexibility costs risk-averse manufacturers more.*

The average deviation $\hat{a}$ of manufacturing stages during the capacity project phase is furthermore reduced for the CF strategy. The effect is more pronounced for the risk-neutral manufacturer.

Observation 4.6. *Central capacity fixing reduces the deviation in the configuration of the manufacturing stages in time-phased decision making during capacity planning projects.*

We also observe that the average configuration $\bar{a}$ is greater for a manufacturer applying the CF strategy than it is in the NCF case. Thus, the CF strategy results in relatively high capacity levels compared to the optimal configuration found without central capacity fixing. This effect is observed for risk-neutral and risk-averse manufacturers, however, weakened in the risk-averse case.

Observation 4.7. *The central capacity fixing practice increases the sensitivity to the risk attitude.*

4.5.4. Impact of modularization

To answer question 3, we consider two layout types capturing the impact of the current modularization trend in the automotive industry on the body shop's process flexibility

Table 4.2: Overview of results for central capacity fixing.

Risk	Strategy	NPV, CVaR	$\bar{a}$	$\hat{a}$
Neutral	NCF	100.0%	2.47	0.28
	CF	99.6%	2.56	0.25
Averse	NCF	100.0%	2.37	0.30
	CF	97.9%	2.41	0.17

(cf. Section 4.3). Let L_1 be the conventional layout with a dedicated body shop $j \in J = V$ for every derivative $v \in V$, as defined for the original CPM(R)-LCM in Section 4.4. Let L_2 be a layout using one flexible body shop shared by all derivatives V. For L_2, we use a modified version of the CPM(R)-LCM based on the set of shared stages $I^{L_2} = I \cup \{4\}$ ($i = 4$ denotes the flexible body shop). We set $f_4^{I^{L_2}} = \min_{j \in J}\{f_j^J\}$, $\theta_{4t}^{I^{L_2}} = \theta_{j^*t}^J$ with $j^* = \arg\min_{j \in J}\{f_j^J\}$, and $J^{L_2} = \emptyset$ ($\theta_{it}^{I^{L_2}} = \theta_{it}^I \; \forall i \in I^{L_2} \setminus \{4\}$).

To compare L_1 and L_2, we used a modified design of experiments: For every instance that the CPM(R)-LCM solved for L_2 we varied the investment costs, $\lambda_4^{I^{L_2}}(a)$, by the investment costs ratio, κ, of the body shop's total investment costs in L_1 assuming the same configuration $a \in A$, i.e. $\lambda_4^{I^{L_2}}(a) = \kappa \sum_{j \in J} \lambda_j^J(a)$. For L_2 we assume identical production costs and workforce requirements in the LCM. Thus, we ignore scale and synergy effects such as increased flexibility to react to uncertainties during the lifecycle by production leveling. Below, we analyze the break-even investment-costs ratio and the hidden costs of flexible body shops:

1. The break-even point κ^* (κ^{R*}) is defined as

$$\kappa^* = \max\{\kappa | NPV^{L_2}(\kappa) \geq NPV^{L_1}\}, \quad \kappa^{R*} = \max\{\kappa | CVaR^{L_2}(\kappa) \geq CVaR^{L_1}\}. \tag{4.12}$$

2. The hidden costs of a flexible body shop ξ (ξ^R) are defined as

$$\xi^{(R)} = 100 - \kappa^{(R)*}. \tag{4.13}$$

NPV^{L_1} and NPV^{L_2} ($CVaR^{L_1}$ and $CVaR^{L_2}$) are the NPV (CVaR) that the CPM(R)-LCM determines for L_1 and L_2, respectively.

Figure 4.9 shows that the average κ^* is 80.8%. Thus, assuming risk-neutral decision making, the flexible body shop in L_2 only becomes superior for investment costs of 80.8% or less of the total investment costs of L_1. The 19.2% gap is the average ξ. It describes all cases of κ for which L_1 has higher body shop investments than L_2, but is
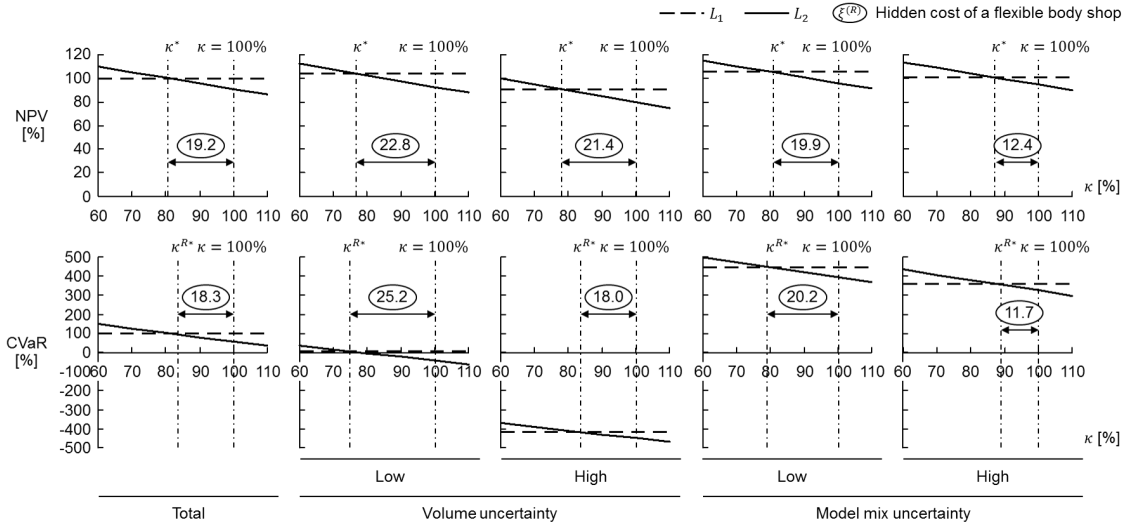
Figure 4.9: Overview of results for dedicated body shops (L_1) and a flexible body shop (L_2).

still the superior layout with respect to the total NPV. For risk-averse decision making, the average ξ^R is slightly lower at 18.3

$\xi^{(R)}$ is specifically observed in time-phased decision making and combines two effects. The first effect results from the reduction of decision flexibility. Each dedicated body shop $j \in J^{L_1}$ has a separate capacity fixing period. Thus, for the shops with fixing periods at a later time point, additional forecast information is observed and the decision can be revised later, whereas the configuration of the flexible body shop $i = 4$ in L_2 must be decided for all derivatives simultaneously, i.e. when the first body shop decision is due for L_1. The second effect results from investment timing. Investment for dedicated shops is distributed over several periods in the capacity project phase. Assuming a discount factor $\beta < 1$, all investment costs in L_1 for body shops j with fixing periods later than the fixing period of the flexible body shop in L_2, are discounted over a longer period, thus, resulting in reduced investment costs during period 0.

Observation 4.8. *Flexible body shops come at a hidden cost under time-phased decision making in capacity planning projects, which results from reduced decision flexibility and discounting.*

Figure 4.9 further indicates an interesting behavior of $\xi^{(R)}$ with respect to uncertainty. For both uncertainty types and both risk attitudes, it shows a $\xi^{(R)}$ reduction for scenarios with high uncertainty levels. For risk-neutral manufacturers, ξ becomes particularly large in an environment of volume uncertainty. The reason is the increased decision-

making flexibility for the automotive manufacturer leading to a better configuration, tailored to the most recent forecast update, for the dedicated body shop $j \in J^{L_1}$ with a fixing period after the fixing of the flexible body shop $i = 4$ in L_2. However, in an environment of model mix uncertainty, ξ diminishes with increasing uncertainty level. The reason for this behavior is the absorption of model mix variations by the flexible body shop $i = 4$ in L_2. Total volume stability in settings representing model mix uncertainty (C and D), neutralizes the effect of increased decision flexibility. Furthermore, ξ^R is significantly reduced in both cases of high uncertainty compared to the case of respective low uncertainty. Flexible body shops thus have a greater impact in uncertain environments for a risk-averse manufacturer.

Observation 4.9. *A flexible body shop is more attractive in an environment with high uncertainty than in one with low uncertainty.*

4.6. Conclusion and managerial implications

In this chapter we focused on capacity planning projects in the automotive sector. Demand uncertainty and high investment costs expose manufacturers to high risk. Investment decisions are time-phased over several years and interact with demand forecasting through a process providing annual updates.

To avoid the complexity of time-phased decision making, automotive manufacturers practice central capacity fixing. They freeze the capacity configuration for all of a derivative's manufacturing stages at a specific time during the project to prevent misalignment in the multi-stage manufacturing process. Hence, we developed an innovative modeling approach to support time-phased decision making. It combines an MDP model of the capacity planning phase and a MILP model of the lifecycle phase. To capture risk attitudes we adapted the CVaR decomposition to time-phased decision making.

The application of our approach to a typical capacity planning problem for a new vehicle introduction with three derivatives led to several findings. We first showed that our approach increases automotive manufacturers' overall performance. Risk-averse manufacturers particularly benefit from our approach. In general, our approach is especially valuable in volatile environments.

When investigating central capacity fixing, we found that a central capacity fixing mechanism significantly reduces deviation in the configuration of manufacturing stages during time-phased capacity planning. However, it also reduces manufacturers' performance, as the planning flexibility is reduced. Risk-averse manufacturers in particular

suffer from the loss of decision flexibility.

Finally, we investigated the effect of vehicle modularization on time-phased capacity planning. Manufacturers have modularized vehicle design thereby enhancing pooled capacity use. This has enabled the introduction of flexible body shops. Flexible body shops require more versatile and costly equipment, but also profit from economies of scale and allow for pooling during the lifecycle. However, the hidden costs of flexible body shops are often ignored in discussions about process flexibility in automotive manufacturing. They result from a loss in decision flexibility in time-phased decision making. Manufacturers must commit early on to a flexible body shop's capacity level. For dedicated body shops, in contrast, investment decisions for derivatives with later SOPs can be made later.

Our numerical study showed significant hidden costs for flexible body shops, which are a strong driver for dedicated body shops. This effect's impact decreases, when uncertainty during the planning phase (especially the model mix uncertainty) is great.

The work presented in this chapter opens several directions for future research. We consider the time-phased planning of multi-stage manufacturing capacities in long-term projects based on regularly updated demand forecasts. Although we discuss the automotive industry, other manufacturing sectors such as the semiconductor or the pharmaceutical industries face similar conditions when making investment decisions. Our approach can be adapted to such settings.

Finally, our approach exemplifies a methodology that integrates project planning and cyclic planning used for recurring business processes. This coordination problem is encountered in many contexts at automotive manufacturers and elsewhere. Our approach can serve as a prototype for the required coordination mechanisms.

Chapter 5.

Balancing benefits and flexibility losses in platform planning

Manufacturers using product platforms target economies of scale and scope. However, they face the challenge of a reduced ability to react to a dynamic environment, because a platform provides the technological basis for all assigned products. When manufacturers launch new platforms, the timing is crucial. Technological innovations that have been successfully developed prior to the platform launch can be incorporated into the platform. A higher level of innovation increases the revenues. After the platform launch, the individual product development can be initiated. A shorter development time increases the development costs. As a consequence, manufacturers have to trade-off increased revenues due to a higher level of innovation against increased development costs due to expedited product development. This chapter introduces a stylized optimization model for this dynamic platform planning problem based on a stochastic process for capturing the uncertainty of innovations. We find that the optimal policy for the platform launch is a time-dependent threshold of the observed innovation level. Based on a case from the automotive industry, we find that manufacturers can suffer a loss of flexibility that significantly reduces platform benefits. It even outweighs the economies of scale. Hence, manufacturers have to weigh properly the trade-offs to ensure that the combined effect of scale and scope economies does lead to a positive impact of platforms. In particular, during the product-to-platform assignment, manufacturers need to consider the loss of flexibility, which depends on the product introduction schedule and the product heterogeneity of the products assigned to a platform.

5.1. Introduction

For a long time, product platforms have been considered as an effective mitigation strategy to address the increasing product variety of technology-based products. However, many manufacturers have recently begun to question their platform strategies, as benefits often fail to materialize. Well-known problems of platforms include product cannibalization, as experienced by GM in the 1980s, and high quality costs, as faced by Toyota in 2010. More recently, the loss of ability to adapt to dynamic market environments has become a concern of manufacturers. As a consequence, some companies have abandoned platforms, as seen in the case of Black and Decker (Boas et al., 2013; Pasche and Sköld, 2012).

A product platform is a common architecture shared by multiple products and provides the technological foundation for them (Meyer et al., 1997). Due to the increased standardization, manufacturers target several benefits: Scale economies are cost benefits resulting from the increased volume of shared parts or processes, for example in manufacturing; scope economies are cost benefits resulting from the increased number of products sharing processes or resources, for example in product development; other benefits can be increased process flexibility or reduced development time (Robertson and Ulrich, 1998).

By diversifying each product's appearance and performance on a platform, manufacturers can still address different customer segments. In industries such as the car, aircraft, or electronics sector, the diversity of products often requires that a manufacturer has multiple platforms (de Weck, 2006). An example is the current platform strategy of *Mercedes-Benz* with four platforms, each implementing a different powertrain concept (Daimler, 2015), i.e. rear-wheel drive, front-wheel drive, off-road drive, and dynamic drive. The Modular Rear-Wheel Drive Architecture (MRA), for instance, is shared by three passenger car models ranging from the mid-size segment to the executive car segment.

Providing the technological foundation for all its products, the platform enforces a common technological solution and therefore limits the degree of freedom to tailor the level of innovation to the customers of a product. Customers, however, recognize the level of technological innovation employed by the platform, as it is highly relevant for the product quality and performance (Pasche and Sköld, 2012). For example in the automotive industry, platforms must be developed to enable new technologies for autonomous driving and electrification. The sensitivity of the customers generally varies across dif-

ferent segments: High-end customers expect a highly innovative, sustainable product and are willing to pay a premium price; low-end customers expect basic functionality for a reasonable price.

Furthermore, technological innovations are developed separately from the platform and its products. Innovations are typically the result of dedicated long-term R&D projects and must be introduced into the process of platform planning (Muffatto, 1999). Nevertheless, research progress is difficult to predict in terms of the timing and extent of an innovation. Thus, the availability of any innovation is subject to uncertainty.

As a consequence, manufacturers of technology-based products are confronted with the problem of *dynamic platform planning*: After having assigned each product to a platform, the manufacturer has to decide for each platform, when to release it in order to enable the individual product development projects. This decision is based on the status of the innovations under development. We refer to this decision as the *platform launch*.

The schedule of the SOP of the products is typically determined earlier than the *platform launch* decision and is often driven by customer expectations or by the SOP of competitor products. Thus, the *platform launch* determines the time available for individual product development. The earlier the *platform launch*, the more time remains for individual product development projects, enabling a resource-efficient and cost-optimal project schedule. Hence, an earlier *platform launch* reduces development costs.

On the other hand, if an innovation project is successfully completed before a platform is launched, it can be incorporated into the platform and, therefore, be made available to the products sharing the platform. As customers are sensitive to the level of innovation, the manufacturer can achieve a higher sales volume. Thus, a late *platform launch* increases the potential to incorporate innovations into the platform and, consequently, enhances the revenue.

Determining the right timing for the *platform launch* is challenging for two reasons. First, the products sharing the platform differ in their sensitivity to the level of innovation: For high-end products it is beneficial to delay the *platform launch* in order to realize a higher level of innovation. For low-end products it is beneficial to launch the platform early, based on a lower level of innovation, in order to achieve low development costs. Second, SOPs are often scheduled in a sequential manner over a longer period of time in order to prevent cannibalization and avoid the increased complexity of simultaneous ramp-ups: For products with a later SOP it might be beneficial to wait for innovations, while for products with an earlier SOP the timeframe for the individual

product development is compressed causing very high costs.

To support manufacturers of technology-based products in platform planning, we make the following contributions: We identify the *dynamic platform planning* problem as a cyclic planning process that determines the timing of the *platform launch* for technology-based products with heterogeneous sensitivity to innovation, phased SOP schedules, and an exogenous, uncertain R&D process providing technological innovations. Furthermore, we propose a stylized optimization model that supports *dynamic platform planning*.

We derive and characterize the optimal policy for the *platform launch* as a threshold for technological innovation: Imagine a manufacturer with the intention to launch a platform that employs certain product innovations currently under development. The manufacturer observes the outcome of the R&D projects that target these innovations. The threshold determines whether the manufacturer should keep waiting for innovations or should launch the platform now based on the current level of innovation, depending on how much time is left until the platform products are expected in the market. We show that there is an optimal, threshold-based policy for the *platform launch* and characterize its behavior.

Furthermore, based on the case of the MRA platform of *Mercedes-Benz*, we identify and characterize the *loss of flexibility* associated with platforms for technology-based products with different sensitivity to innovation. This *loss of flexibility* results from the compromise in the level of technological innovation made at the *platform launch* and reduces the well-known platform benefits.

Our results show that scale economies alone cannot compensate for the *loss of flexibility* associated with the introduction of platforms. In order to achieve a positive impact of platforms, manufacturers must also realize scope economies.

The extent of the *loss of flexibility* depends on the SOP schedule and is small for a "high profit first" approach: If possible, set the SOPs for the products within a platform in the order of the product's profitability, from highest to lowest. If the SOPs cannot be influenced, a manufacturer must consider the increased *loss of flexibility* during the product-to-platform assignment; a reassignment taking the SOP schedule into account may be beneficial. Furthermore, the *loss of flexibility* increases, if products of the same platform significantly differ in terms of the sensitivity of their customers to innovation.

Our results further show that in a multi-platform strategy the product-to-platform assignment has significant impact on the *loss of flexibility*. Thus, a careful consideration of the *loss of flexibility* based on the SOP schedule is necessary, when a manufacturer assigns products to platforms.

Section 5.2 gives an overview of the related literature. Section 5.3 presents the stylized optimization model for *dynamic platform planning*. Section 5.4 presents our theoretical results on the optimal threshold-based policy for the *platform launch*. Section 5.5 demonstrates the findings of our numerical experiments on the threshold-based policy for the *platform launch* and on the *loss of flexibility* due to platforms. Section 5.6 gives a summary and conclusion.

5.2. Literature review

The problem of *dynamic platform planning* is related to two research streams: product platform planning and product replacement planning.

There is a broad body of literature on the planning of product platforms (cf. Jiao et al., 2007; Zhang, 2015). Most of the existing literature focuses on the platform design.

Single-platform design is concerned with determining the set of common platform variables and their design for a product family in order to achieve the platform benefits, i.e. scale economies and scope economies (Simpson et al., 2001). Krishnan and Gupta (2001) study the scale and scope economies due to platforms and weigh them against the loss of diversification resulting from overdesigning the low-end variant of the platform; Krishnan et al. (1999) consider the scope economies based on shared resources and processes in the development of technology-based products. Other scope economies can be increased adaptability in product design (Suh et al., 2007), reductions in time-to-market (Cohen et al., 1996), or increased process flexibility in manufacturing (Simpson et al., 2012). Furthermore, Van den Broeke et al. (2018) study different levels of flexibility in *platform design* and find that investing into a flexible platform, i.e. a platform not specialized for one of the product segments, can be optimal and reduces the investment risk.

Multi-platform design extends the platform design problem to the case of multiple parallel product platforms and therefore focuses on determining the number of platforms and the assignment of products to platforms (de Weck, 2006). Multiple platforms are necessary, if the product scope exceeds a certain level of diversification (de Weck et al., 2003). Existing literature studies the assignment of products to platforms based on similarities in the manufacturing process (cf. Ben-Arieh et al., 2009; Morgan et al., 2001a), based on product positioning (cf. Kumar et al., 2009), or based on total costs for supply chain, platform development, and customization (cf. Van den Broeke et al., 2015). Due to the increased complexity of multi-platform design, meta heuristics are

the preferred solution method (Van den Broeke et al., 2017).

The literature on platform design focuses primarily on the question of whether it is beneficial or not to introduce a platform. Only a few papers consider when to introduce or replace a platform. Kang et al. (2012) focus on the replacement strategy for a platform given several successor products. They investigate the optimal platform lifetime based on a dynamic program that trades-off reduced development costs of the platform against the lost sales due to obsolete technology. Van den Broeke and Boute (2017) apply a simulation model to analyze the platform replacement frequency assuming the same context. They find a strong dependency of the replacement frequency on the performance objectives of a firm. Both approaches focus on several product generations with only one product being produced at a time. Our approach focuses on a different type of problem, as it is more short-term (only one product generation) and considers multiple heterogeneous products offered simultaneously with phased lifecycles and time-dependent development costs.

There is a stream of literature focusing on the dynamics of new product introduction without platforms: The product replacement problem determines when to replace an old product generation by a successor product based on several factors. Two of these factors are important for the problem of *dynamic platform planning*.

First, the costs for the development of a new product depend on the duration of the development project. The development costs are typically a convex function of the development time (Graves, 1989). Given the cost-optimal development time, shortening the product development projects increases the development costs, as more resources must be used and more coordination is necessary. Examples for development cost functions assuming such a behavior can be found in Morgan et al. (2001b), Druehl et al. (2009), and Liao and Seifert (2015).

Second, a higher level of innovation increases the demand for the new product. Innovations are typically developed in separate long-term R&D projects that are subject to uncertainty with respect to success and completion timing. Therefore, product innovations in the product replacement problem are typically based on the assumption of an exogenous, uncertain R&D process (Gjerde et al., 2002). For example, Krankel et al. (2006) use a Markov process to capture stochastic product innovations and model the market potential in dependency of the level of innovation employed by the new product. Further examples can be found in Liu and Özer (2009), Lobel et al. (2016), and Kirshner et al. (2017).

Other relevant factors for the product replacement are the mismatch between supply

and demand (Li and Graves, 2012) and the demand substitution during the transition period (Ke et al., 2013; Li et al., 2010).

However, research focusing on product replacement does not account for important characteristics of platforms: With the timing of the *platform launch* the manufacturer sets the innovation level of the platform. Hence, the same level of technology is shared by multiple products that focus on different price segments and may have phased lifecycles. The manufacturer has to find a compromise in the level of innovation for all products sharing the same platform in order to achieve scale and scope economies. Our approach bridges the field of product replacement and the field of platform planning in order to close this gap and study the problem of *dynamic platform planning.*

5.3. A model for dynamic platform planning

We present a dynamic programming model for the problem of *dynamic platform planning* at a manufacturer of technology-based products employing a multi-platform strategy. The model determines the timing of the *platform launch* during the time window of length T periods up to the time of the earliest SOP. All symbols used in the model can be found in Appendix B.1. We make the following assumptions:

1. The product-to-platform assignment is given; we focus on one platform of the manufacturer with assigned products $m \in M$ that target different customer segments and therefore vary in profitability π_m.

2. The SOP for each product is given, denoted as τ_m for product m. We assume that each product has the same lifecycle of σ periods, and we do not consider successor products. The *platform launch* can occur in any period $t \in \{0, 1, ..., T - 1\}$ with $T = \min\{\tau_m\}$, i.e. the *platform launch* must occur prior to the earliest SOP.

3. The level of innovation is a stochastic process that increases with successfully developed technological innovations. Technological innovations are supplied by exogenous R&D projects subject to uncertainty; random variable $\zeta_t \in \{0, 1, 2, ...\}$ defines the incremental level of innovation that the manufacturer gains in period t and follows distribution ϕ.

4. Demand volume for product m is an increasing, concave function in the level of innovation employed by product m.

5. Product-specific development of product m can only be initiated after the *platform launch* and has to comply with the given SOP schedule τ_m. The nominal development time is λ periods. Shorter development times incur additional costs that increase as a convex function of the time reduction.

Assumption 1 and 2 reflect the planning hierarchy seen in industrial practice. The product-to-platform assignment and the SOP schedule are determined earlier than the *platform launch*. Furthermore, the SOP schedule is driven by customer expectations and competitor schedules. Thus, a time-pacing product development strategy with given lifecycle parameters applies and successor generations are not relevant for the scope of the proposed model.

Assumption 3 describes the exogenous R&D process supplying technological innovations in dedicated projects with uncertain success and timing. ζ_t can be interpreted as the number of innovation projects successfully completed in period t, for example measured by the number of patents registered in period t. Thus, for every period that the manufacturer decides to postpone the *platform launch*, the technology level that is available for the platform increases by the realization of ζ_t.

Assumption 4 is in line with existing literature (e.g. Krankel et al., 2006; Liu and Özer, 2009), as a more innovative product for the same price will attract more customers; furthermore, an incremental innovation employed in a more innovative product attracts less customers than an incremental innovation employed in a less innovative product.

Assumption 5 reflects the existing literature that product development costs are a convex function of development time (cf. Graves, 1989).

We formulate the *dynamic platform planning* problem as a T-horizon MDP with state variable z_t and decision variable x_t. State variable $z_t \in \{0, 1, 2, ...\}$ indicates the current level of technological innovation available to the manufacturer based on the exogenous R&D process. It describes the number of innovations that have been successfully developed by the manufacturer's R&D department and is defined as $z_{t+1} = z_t + \zeta_t$.

In every period t, the manufacturer observes $z_t \in \{0, 1, 2, ...\}$ and decides whether to launch the platform employing the current level of innovation z_t, $x_t = 1$, or delay the *platform launch* and wait for further innovations, $x_t = 0$. The technology level of the products $m \in M$ is set by the level of innovation of the platform, z_t, at the time of the *platform launch*.

If the platform is launched in period t $(x_t = 1)$, the manufacturer realizes the profit-to-go $I_t(z_t)$,

$$I_t(z_t) = -D_t + \sum_{m \in M} P_{mt}(z_t). \tag{5.1}$$

I_t is the sum of the total lifecycle profits $P_{mt}(z_t)$ of products $m \in M$ net the total development costs D_t, assuming that the platform employs innovation level z_t and that the product-specific development can be initiated as of time t.

If the platform is not launched in period t $(x_t = 0)$, the manufacturer realizes the profit-to-go $H_t(z_t)$,

$$H_t(z_t) = 0 + \beta E_\phi[V_{t+1}(z_t + \zeta_t)]. \tag{5.2}$$

H_t is the expected value of next period's value functions V_{t+1} (assuming optimal behavior in $t + 1$) based on discount factor $\beta \in [0, 1]$ and random variable ζ_t.

Consequently, the value function in period t is defined as

$$V_t(z_t) = \max\{H_t(z_t), I_t(z_t)\}. \tag{5.3}$$

The optimal solution of the resulting dynamic program is found by applying the Bellman principle, where we assume a termination value of $V_T = 0$ in period T, as not launching the platform implies zero profits.

The central trade-off in *dynamic platform planning* is between the lost sales due to a low technology level (early *platform launch*) and the increased development costs due to compressed development time (late *platform launch*). In order to capture this trade-off in (5.1), we define the profits $P_{mt}(z_t)$ earned by product m based on innovation-sensitive demand and the time-sensitive development costs D_t in the following sections. Furthermore, we discuss how cost benefits can be considered.

5.3.1. Modeling profits based on innovation-sensitive demand

In order to express the lifecycle profits P_{mt}, we first have to establish the underlying demand model that captures the sensitivity of the demand to the level of innovation. We assume that for each product m, demand occurs at a constant rate $\delta_m(z_t)$ over the lifecycle of the product. This demand rate is characterized by two types of customers: customers insensitive to the level of innovation z_t (i.e. the base customers), which we capture by demand magnitude η_m, and customers sensitive to the level of innovation z_t, which we capture by growth rate ξ_m. Based on η_m and ξ_m, we define the innovation-

sensitive demand rate for product m, $\delta_m(z_t)$, as

$$\delta_m(z_t) = \eta_m z_t^{\xi_m}, \tag{5.4}$$

where we assume $\eta_m > 0$, $0 \leq \xi_m \leq 1$ and $z_0 = 1$ in order to satisfy Assumption 4.

The profit P_{mt} earned by the manufacturer during the lifecycle of product m can now be defined as

$$P_{mt}(z_t) = \sum_{t'=\tau_m}^{\tau_m+\sigma-1} \beta^{t'-t} \pi_m \delta_m(z_t), \tag{5.5}$$

where π_m is the constant profit per unit of product m and $\delta_m(z_t)$ is as defined in (5.4). Thus, P_{mt} is the NPV in period t of the profits generated by product m employing innovation level z_t, given the platform is launched in period $t < \tau_m$.

5.3.2. Modeling time-sensitive development costs

We express the development costs D_t as a function of the development time available between the *platform launch* and the SOPs of the products, in terms of the following three parameters: ϑ represents the total development costs for all products $m \in M$ assuming the nominal development time of λ periods; κ and α describe the incremental development costs, when the development time is less than the nominal development time λ. κ can be interpreted as the incremental development costs for expediting the development project by one period and α represents the growth of the costs, if the residual development time is further reduced.

We define the total development costs D_t as

$$D_t = \vartheta + \sum_{m \in M} \kappa y_{mt}^\alpha, \tag{5.6}$$

where $y_{mt} = [\lambda - (\tau_m - t)]^+$ is the level of expediting and $[u]^+ = \max\{u, 0\}$. Thus, D_t is the sum of the nominal development costs and a time-sensitive penalty term for expedited development. The penalty term determines the increased development costs for each of the products, if the time available for the development of product m, $(\tau_m - t)$, is less than λ periods. We assume $\kappa \geq 0$ and $\alpha \geq 1$ in order to comply with Assumption 5.

Note that λ is the the preferred development duration. Thus, if the platform is launched at period t and the time available for the development of product m, $(\tau_m - t)$, exceeds λ, the duration of the associated development project is still λ periods.

5.3.3. Modeling cost benefits of platforms

We now characterize the cost benefits of a platform in the context of our model, namely scale economies and scope economies.

Scale economies are driven by the platform volume that can lead to a reduction of the unit costs based on learning. Thus, we follow the common concept of the learning curve and assume that the unit costs are a convex function decreasing in the cumulative volume of shared components or of shared processes related to the platform (cf. Yelle, 1979).

The cumulative platform volume increases with the level of innovation of the platform, z_t, set by the timing of the *platform launch*. Furthermore, only the platform-related share of the unit costs, i.e. the costs that accrue due to common processes or parts of the platform, are subject to the relevant scale economies. Thus, we assume platform-related unit costs as a convex function decreasing in z_t.

To include the platform-related scale economies in (5.5), we add a term for incremental profits per unit due to scale economies, $\gamma(z_t)$:

$$P_{mt}(z_t) = \sum_{t'=\tau_m}^{\tau_m + \sigma - 1} \beta^{t'-t}[\pi_m + \gamma(z_t)]\delta_m(z_t). \tag{5.7}$$

γ is a concave function increasing in the level of innovation z_t. This follows immediately from the convexity of the unit costs in z_t. We note that scale economies also apply for the non-platform case and are computed separately for every product m.

Scope economies depend on the number of products sharing the platform and, therefore, sharing some of the resources and processes. In product development, for example, steps in the individual product development process are simplified or may become redundant (Krishnan et al., 1999), e.g. due to increased reuse of parts and facilities, increased transfer of knowledge and experience, reduced testing efforts, etc. Thus, we assume there will be reductions in regular development cost ϑ and in the penalty cost for expedited development κ due to products sharing a platform.

In our analysis and experiments presented in the following, we considered scale and scope economies, if they apply, based on these assumptions. More details on the implementation of the cost benefits are given in Appendix B.2.

5.4. An optimal threshold-based policy for the platform launch

In this section, we analyze the structural properties of an optimal policy for the *platform launch* based on its relation to the technological innovations provided by R&D. More precisely, we show that if the level of technological innovation observed by the manufacturer reaches a certain innovation threshold z_t^*, it is optimal for the manufacturer to launch the platform, even if other innovations are expected to become available. Recall that the platform employs the level of innovation seen by the manufacturer at the time of the *platform launch*. Thus, if the threshold z_t^* is reached, the incremental development costs for a further delay of the *platform launch* have surpassed the incremental profit originating from the additional volume due to the expected technology advancement.

Furthermore, the level of the threshold z_t^* is declining over time. Thus, if the manufacturer delays the *platform launch*, the incremental expected profits due to the delay decline compared to the previous period (due to the decreasing incremental demand volume in z_t), while the incremental development costs grow.

To prove the existence of such a threshold z_t^*, we require the property of I_t established by Lemma 5.1. Note that we substitute $\beta'_{tm} = \sum_{t'=\tau_m}^{\tau_m+\sigma-1} \beta^{t'-t}$ in the following calculus. Furthermore, in the following proofs we drop the subscript t in z_t, where it is not required.

The following result characterizes the profit-to-go function, in case the platform is launched, $I_t(z_t)$. In Lemma 5.1, we show that the incremental profit earned by a higher level of innovation is positive and decreases with the innovation level z_t.

Lemma 5.1. *$I_t(z_t)$ is a function increasing and concave in z_t.*

Proof of Lemma 5.1. It is sufficient to show that $\Delta_z I_t(z) \geq 0$ and $\Delta_{z^2} I_t(z) \leq 0$. We proceed by calculation.

$$
\begin{aligned}
\Delta_z I_t(z) &= I_t(z+1) - I_t(z) \\
&= \sum_{m \in M} P_{mt}(z+1) - \sum_{m \in M} P_{mt}(z) \\
&= \sum_{m \in M} \beta'_{tm} \Big[\big[\pi_m + \gamma(z+1) \big] \delta_m(z+1) - \big[\pi_m + \gamma(z) \big] \delta_m(z) \Big] \geq 0
\end{aligned}
$$

The last inequality results from Assumption 4, as $\delta_m(z)$ is increasing in z and $\gamma(z)$ is increasing in z. Furthermore, $\Delta_{z^2} I_t(z) \leq 0$ is fulfilled, if for every product m the

expression

$$\left[\left[\pi_m + \gamma(z+1) \right] \delta_m(z+1) - \left[\pi_m + \gamma(z) \right] \delta_m(z) \right]$$

is a decreasing function of z, which immediately results from Assumption 4, as $\delta_m(z)$ and $\gamma(z)$ are concave functions of z. $\qquad\square$

Now we are able to prove the existence of the innovation threshold z_t^* characterizing an optimal *platform launch* policy. The manufacturer chooses between waiting ($x_t = 0$) and launching the platform with the current level of innovation z_t ($x_t = 1$). In accordance with Krankel et al. (2006), the threshold z_t^* exists, if the gap between the profit-to-go functions for waiting, $H_t(z_t)$, and for launching the platform, $I_t(z_t)$, decreases in the level of innovation z_t.

Proposition 5.1. *For every period $t \in \{0, 1, ..., T\}$ there exists a threshold for the level of innovation, z_t^*, such that the platform launch is optimal if and only if the current level of innovation $z_t \geq z_t^*$.*

Proof of Proposition 5.1. We need to show that if $H_t(z) \leq I_t(z)$, then it is true that $H_t(z+1) \leq I_t(z+1)$ for all z. To show this, it is sufficient to show that $\Delta_z[H_t(z) - I_t(z)] \leq 0$ for every $z \in \{0, 1, 2, ...\}$ in period t. We proceed by induction. In period $t = T - 1$, based on Assumption 2,

$$H_{T-1}(z+1) = H_{T-1}(z) = 0$$

for any $z \in \{0, 1, 2, ...\}$, as the platform is not launched in $t < T$ and therefore no profit is generated; hence,

$$\Delta_z[H_{T-1} - I_{T-1}] = 0 - [I_{T-1}(z+1) - I_{T-1}(z)] \quad \leq 0,$$

where the last inequality results from Lemma 5.1. Thus, we assume

$$\Delta_z[H_{t'}(z) - I_{t'}(z)] \leq 0 \tag{5.8}$$

is true for every $z \in \{1, 2, ...\}$ in period t' in the backwards iteration of the dynamic program. It remains to be shown that (5.8) still holds for the next backwards iteration

in the dynamic program, i.e. for period $t = t' - 1$:

$$\Delta_z[H_{t'-1}(z) - I_{t'-1}(z)] = H_{t'-1}(z+1) - I_{t'-1}(z+1) - H_{t'-1}(z) + I_{t'-1}(z)$$
$$= \beta E_\phi[V_{t'}(z+1+\zeta_{t'-1}) - V_{t'}(z+\zeta_{t'-1})] - [I_{t'-1}(z+1) - I_{t'-1}(z)]$$
$$= \beta E_\phi[\max\{H_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+1+\zeta_{t'-1}), 0\} + I_{t'}(z+1+\zeta_{t'-1})$$
$$- \max\{H_{t'}(z+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1}), 0\} - I_{t'}(z+\zeta_{t'-1})]$$
$$- [I_{t'-1}(z+1) - I_{t'-1}(z)]$$

Note that we use the substitution $V_t(z) = \max\{H_t(z) - I_t(z), 0\} + I_t(z)$. We continue as follows:

$$\Delta_z[H_{t'-1}(z) - I_{t'-1}(z)] = \beta E_\phi[\max\{H_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+1+\zeta_{t'-1}), 0\}$$
$$- \max\{H_{t'}(z+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1}), 0\}$$
$$+ I_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1})]$$
$$- [I_{t'-1}(z+1) - I_{t'-1}(z)]$$
$$= \beta\Big[E_\phi[\max\{H_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+1+\zeta_{t'-1}), 0\}]$$
$$- E_\phi[\max\{H_{t'}(z+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1}), 0\}]$$
$$+ E_\phi[I_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1})]\Big]$$
$$- [I_{t'-1}(z+1) - I_{t'-1}(z)].$$

From the induction assumption in (5.8) it is clear that

$$E_\phi[\max\{H_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+1+\zeta_{t'-1}), 0\}]$$
$$-E_\phi[\max\{H_{t'}(z+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1}), 0\}] \quad \leq 0.$$

Thus, to complete the induction argument it is sufficient to show that

$$\beta E_\phi[I_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1})] - [I_{t'-1}(z+1) - I_{t'-1}(z)] \leq 0. \tag{5.9}$$

We continue by applying Lemma 5.1 on the left-hand side of (5.9),

$$\beta E_\phi [I_{t'}(z+1+\zeta_{t'-1}) - I_{t'}(z+\zeta_{t'-1})] - [I_{t'-1}(z+1) - I_{t'-1}(z)]$$

$$\overset{\text{Lemma 5.1}}{\leq} \beta [I_{t'}(z+1) - I_{t'}(z)] - [I_{t'-1}(z+1) - I_{t'-1}(z)]$$

$$= \beta [I_{t'}(z+1) - I_{t'}(z)] - \beta [I_{t'}(z+1) - I_{t'}(z)] = 0,$$

where the inequality results from the concavity of $I_t(z)$ in z. Note that $\Delta I_{t'-1}(z) = \beta \Delta I_{t'}(z)$ as $\beta'_{t'-1,m} = \beta \beta'_{t'm}$. □

Now we are able to characterize the threshold with respect to planning period t, i.e the time moving toward the SOPs.

Proposition 5.2. *The threshold, z_t^*, characterizing the optimal platform launch policy, is decreasing with the planning period $t < min\{\tau_m\}$, for as long as the platform launch remains profitable in the next period ($I_{t+1}(z_t^*) \geq 0$).*

Proof of Proposition 5.2. It is necessary to show that $z_{t_2}^* \leq z_{t_1}^* \ \forall t_2 > t_1$ and for $I_{t_1+1}(z_{t_1}^*) \geq 0$. We proceed with proof by contradiction. Assume $\exists t_2 > t_1$ such that $z_{t_2}^* > z_{t_1}^*$. As both $z_{t_1}^*$ and $z_{t_2}^*$ are thresholds for the *platform launch*, the following relation between development costs D_t and lifecycle profits P_{mt} has to apply for $t = t_1$ and $t = t_2$:

$$\Delta_t D_t \geq E_\phi \Big[\Delta_t \sum_{m \in M} P_{mt}(z_t^*) \Big]. \tag{5.10}$$

It reflects that the incremental costs for waiting another period exceed the incremental profits generated by the expected increase in the technology level. Additionally, the following relation must be true, considering Assumption 5:

$$\Delta_t D_{t_1} \leq \Delta_t D_{t_2}. \tag{5.11}$$

Equation (5.11) results from the convexity property of the time-sensitive development costs, D_t, in t with $t_2 > t_1$. Furthermore, based on Assumption 4, the following must hold for any $z_t' \in [z_{t_1}^*, z_{t_2}^*]$:

$$\Delta_z \sum_{m \in M} P_{mt_1}(z_{t_1}^*) \geq \Delta_z \sum_{m \in M} P_{mt}(z_t'). \tag{5.12}$$

Equation (5.12) results from the concavity property of profits, P_{mt}, in z_t (based on the concavity of the innovation-sensitive demand volumes, $\delta_m(z_t)$, and of the incremental

profit, $\gamma(z_t)$). As $E_\phi[\Delta_t z_{t_1}^*] = E_\phi[\Delta_t z_t'] = E_\phi[\zeta_t]$, i.e. the expected increase of the innovation level is independent of the period and the current level of innovation, the following implication must hold:

$$(5.12) \Rightarrow E_\phi\Big[\Delta_t \sum_{m \in M} P_{mt_1}(z_{t_1}^*)\Big] \geq E_\phi\Big[\Delta_t \sum_{m \in M} P_{mt}(z_t')\Big]. \qquad (5.13)$$

Let us assume $z_{t_2}' = z_{t_2}^* - 1$, i.e. a value below the threshold in t_2 resulting in $x_{t_2} = 0$ (wait), and let us further assume $I_{t_2}(z_{t_2}') \geq 0$, i.e. launching the platform is still profitable. By definition the incremental development costs must be lower than the expected incremental profits:

$$\Delta_t D_{t_2} < E_\phi\Big[\Delta_t \sum_{m \in M} P_{mt_2}(z_{t_2}')\Big]. \qquad (5.14)$$

Thus,

$$E_\phi\Big[\Delta_t \sum_{m \in M} P_{mt_2}(z_{t_2}')\Big] \overset{(5.14)}{\geq} \Delta_t D_{t_2} \overset{(5.11)}{\geq} \Delta_t D_{t_1} \overset{(5.10)}{\geq} E_\phi\Big[\Delta_t \sum_{m \in M} P_{mt_1}(z_{t_1}^*)\Big], \qquad (5.15)$$

where the last implication is a contradiction to Equation (5.13), as $z_{t_1}^* \leq z_{t_2}' = z_{t_2}^* - 1$. Therefore, underlying assumption of $z_{t_2}^* > z_{t_1}^*$ cannot be true and $z_{t_2}^* \leq z_{t_1}^*$ must hold for $t_2 > t_1$ and $I_{t_2}(z_{t_1}^*) \geq 0$. $\qquad \square$

Note that the threshold will start to grow, whenever $I_{t+1}(z_t^*)$ becomes negative, as there will be cases for which not launching the platform at all is the optimal solution. The threshold z_t^* is illustrated and further characterized in the next section.

5.5. Numerical results

Based on the data introduced in Section 5.5.1 we analyze the sensitivity of the innovation threshold for the optimal *platform launch* policy (Section 5.5.2) and investigate flexibility losses that are caused by the compromise made at the *platform launch* (Section 5.5.3).

5.5.1. Data and design of experiments

The data used in the following experiments are based on the case of the *Mercedes-Benz* MRA platform introduced in Section 5.1. The MRA is shared by three products: The C-Class focuses on the lower mid-size segment and has the largest share in the production

Table 5.1: Setting of product parameters in the base case.

Product m	Segment	Price [EUR]	η_m	ξ_m	z_m^{max}	Profit margin
1	High-end	69,000	20,000	0.50	10	0.20
2	Low-end	30,000	200,000	0.00	1	0.05
3	Intermediate	40,000	100,000	0.25	8	0.10

Table 5.2: Setting of other parameters in the base case.

Parameter	α	β	ω [EUR]	ϵ	ϑ^M [EUR]	λ	ρ	σ
Setting	1.5	1.0	14,250	0.0	10^9	8	0.0	12

volume of the platform; the higher priced E-Class addresses the upper mid-size segment with more sophisticated customers; the S-Class is the leading product in the executive car segment and therefore has to satisfy very high expectations on the degree of innovation. The three products entered the market over a timespan of almost three years: The first product release of the MRA was the S-Class in June 2013 with an annual volume of 110,000 units. It was followed by the C-Class in February 2014 (445,000 units per year) and by the E-Class in February 2016 (345,000 units per year).

In the following experiments, we select the C-Class, E-Class, and S-Class as representatives of the lower-mid-size (i.e. low-end), the upper-mid-size (i.e. intermediate), and the executive (i.e. high-end) car segments. We collected publicly available, real world data on SOPs, prices, and volumes based on the price listings provided by *Mercedes-Benz*[1] and on global market data provided by the *IHS Global Insight - Automotive*[2] database. Note that the prices are in EUR, excluding taxes, and for the entry model configuration.

Based on the collected data, we specify a base case for our analysis. We assume a platform planning cycle of six months (i.e. bi-annual periods). Depending on the context of the analysis, we focus on products $M = \{1, 2\}$ (high-end and low-end) or $M' = \{1, 2, 3\}$ (high-end, low-end, intermediate). The product-related data is summarized in Table 5.1. For the demand functions δ_m capturing the innovation sensitivity of products m we assume demand magnitudes η_m, demand growth rates ξ_m, and segment-specific maximum levels of innovation z_m^{max} as shown in Table 5.1. z_m^{max} represents the highest level of innovation that has any impact on the demand in the market segment (i.e. for $z_t > z_m^{max}$ the platform offers an overdesigned technology for the segment of product

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[1] *Mercedes-Benz* Germany: `https://www.mercedes-benz.de/content/germany/mpc/mpc_germany_website/de/home_mpc/passengercars/home/new_cars/beratung___kauf/preislisten.html`.

[2] *IHS Global Insight - Automotive*: `https://www.ihs.com/industry/automotive.html`.

m). For simplicity, if not mentioned otherwise, we norm the level of innovation to the low-end product ($z_2^{max} = 1$), i.e. all customers of the low-end product are insensitive to any additional technological innovations. Furthermore, we assume typical profit margins seen in the associated car segments. The profit margin of product m shown in Table 5.1 is multiplied with the observed price point to receive profit π_m.

Other, non-product-specific data is summarized in Table 5.2. Note that the monetary values are in EUR and time data is based on periods of six months. The development time of four years ($\lambda = 8$) and lifecycle duration of six years ($\sigma = 12$) are common in the automotive industry. The growth rate α of 1.5 reflects the empirical results on time sensitivity of development costs found by Graves (1989): A reduction of one percent in development time causes an increase of one to two percent in development costs.

Scale and scope economies are considered based on the assumptions described in Section 5.3.3. To analyze the influence of scale economies we introduce $\epsilon \in [0, 1]$ as the learning parameter that shapes the decay of the unit costs with increasing cumulative production volume based on the concept of the learning curve. Note that the learning parameter ϵ corresponds to a learning rate of $1 - 2^{-\epsilon}$, which describes the percentage of reduction in unit costs as the cumulative production volume doubles. The learning curve is applied only on the platform-related costs ω, which we assume to be 14,250 EUR (representing 50% of the total costs of the low-end product).

Furthermore, to analyze the influence of scope economies we introduce parameters ϑ^M and ρ. ϑ^M denotes to the regular development costs for a single product, assuming no platform is used. We assume a value of one billion EUR, which represents the typical costs of developing a new car model. $\rho \in [0, 1]$ describes the extent of platform savings in development costs compared to the total regular development costs without platforming (i.e. $|M|\vartheta^M$). For example, $\rho = 30\%$ indicates that in total the manufacturer would save 30% in costs for the development of the products $m \in M$, if they use the focal platform, compared to the case when every product is developed independently.

Details on the implementation of the scale and scope economies are presented in Appendix B.2. In the base case we set ϵ and ρ to zero ignoring the scale and scope economies. Depending on the context of the analysis we vary ϵ and ρ.

The development process for technological innovations is modeled as a binary random variable ζ_t being 0 or 1 with equal probabilities of 0.5. Thus, we assume on average one platform-related innovation per year. This assumption is supported by recent technological developments in the automotive industry: In the case of the MRA, innovations related to the powertrain are relevant. Over the last ten years, *Mercedes-Benz*

has introduced ten such innovations, including the hybrid powertrain, the plug-in hybrid powertrain, and several systems supporting autonomous driving[3]. The observed technology level z_t is bound to the interval $\{1, ..., 10\}$ assuming $z_0 = 1$.

In our analysis we investigate different SOP schedules described by $\Delta\tau_m = \tau_m - \tau_1, m \in \{2, 3\}$, i.e. the time gap between the SOPs of the low-end ($m = 2$) or intermediate ($m = 3$) product and the high-end product. For example, $\Delta\tau_2 = -2$ refers to the case when the low-end product has its SOP two periods (i.e. one year) prior to the high-end product. As $\lambda = 8$ we limit our analysis to cases with $\min_m\{\tau_m\} = 8$.

If not stated otherwise, we use the two-product case with $M = 2$ and ignore the index of $\Delta\tau_m$.

5.5.2. Sensitivity of the optimal threshold-based policy for the platform launch

The threshold z_t^* characterizing the optimal *platform launch* policy established by Proposition 5.1 is illustrated in Figure 5.1. The plot is based on the data described in Section 5.5.1 and assumes simultaneous SOPs ($\Delta\tau = 0$). In every period, it is optimal for the manufacturer to launch the platform, if the observed level of technological innovations z_t is greater than or equal to the threshold z_t^*, and it is optimal to wait for innovations that are currently under development, if the observed level of innovation z_t is lower than the threshold z_t^*.

As stated by Proposition 5.2, the threshold z_t^* is decreasing during the first periods until it hits the minimum innovation level of 1 and stays there for the remaining periods $t < \tau$. With $\lambda = 8$, the development costs are the lowest for a *platform launch* in period 0 and increase in convex manner with t. Thus, the manufacturer is more likely to delay the launch during the first periods in order to reach a higher level of innovation for the platform. In the example of Figure 5.1, from period $t = 4$ on the platform is launched in any case, meaning that the increased development costs due to further delay exceed the expected incremental sales due to additional technological advancements incorporated into the platform.

In Figure 5.2 we plot the change in threshold level as it depends on various factors for the base case. For instance, in Figure 5.2a we consider a change to the SOPs relative to the base case, and show how the threshold changes in each period, relative to the base

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[3]*Mercedes-Benz* Germany: `https://www.mercedes-benz.de/content/germany/mpc/mpc_germany_website/de/home_mpc/passengercars/home/world/innovation/milestones.flash.html`
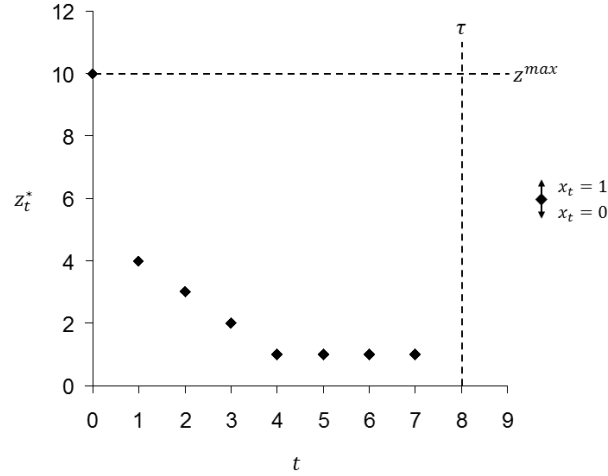
Figure 5.1: Innovation threshold for the platform launch.

case. The following observations on the sensitivity of the innovation threshold z_t^* for the *platform launch* can be made:

Observation 5.1. *The threshold level z_t^* increases for period $t < \min\{\tau_m\}$*

1. *for the case of sequential SOPs (vs. simultaneous),*

2. *with increasing extent of scale economies ϵ,*

3. *with increasing extent of scope economies ρ,*

4. *with increasing innovation sensitivity ξ_1 of the high-end product,*

5. *with decreasing time sensitivity α of the development costs.*

Furthermore, the impact of the number of products $|M|$ sharing the platform on z_t^* is not definite and depends on the underlying SOP schedule and the product positioning of the added product.

SOP schedule

In Figure 5.2a the four cases of sequential SOPs $\Delta\tau \in \{-2, -1, 1, 2\}$ are compared against the base case with simultaneous SOPs ($\Delta\tau = 0$). Recall that $\Delta\tau$ describes the offset between the low-end ($m = 1$) and the high-end product ($m = 2$), e.g. $\Delta\tau = -2$ implies that the low-end product has its SOP two periods earlier than the high-end product. We observe that the innovation threshold z_t^* increases for sequential SOP
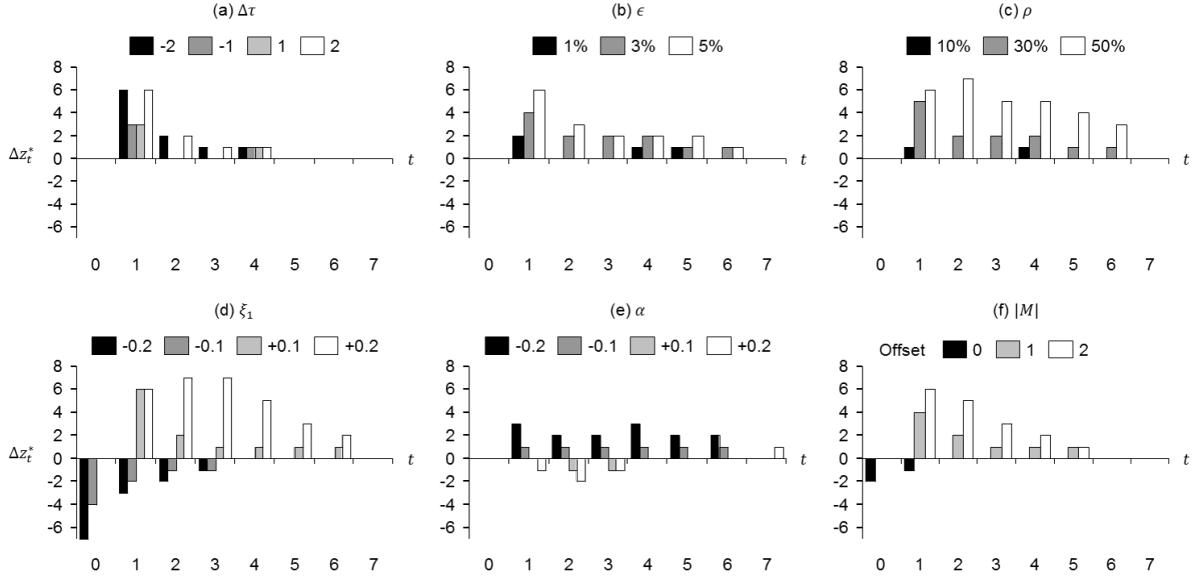
Figure 5.2: Sensitivity of the innovation threshold for the platform launch.

schedules compared to the case of simultaneous SOPs and grows with $|\Delta\tau|$. Thus, the larger the offset between the SOPs of the two products, the higher the threshold becomes, i.e. the later the platform is launched with respect to the earliest SOP.

The reason for this effect is an increase in H_t: Waiting becomes more attractive for product m' with $\tau_{m'} > \min\{\tau_m\}$ due to reduced time-sensitive development costs. Thus, it is important for manufacturers to understand that not merely the earliest SOP among the platform's products defines the *platform launch*, but the overall distribution of the SOPs. This finding applies independently from the sequence in the SOP schedule, i.e. $\text{sgn}(\Delta\tau)$. Thus, it applies for both "high-end first" and "low-end first" schedules. In our experiments no impact of the sequence on the threshold could be observed.

Scale economies

Based on the base case with $\epsilon = 0$, Figure 5.2b shows that the innovation threshold z_t^* increases with the learning parameter ϵ, i.e. with the extent of the scale economies. Thus, the higher the unit cost savings associated with the platform, the higher z_t^* becomes, i.e. the later the platform is launched. The reason for this effect is the sensitivity to innovation of the demand $\delta_m(z_t)$: A higher extent of scale economies makes an incremental unit of demand more attractive and therefore increases H_t. Therefore, increased scale economies delay the *platform launch* and allow the manufacturer to wait longer for innovation projects to be finished.

Scope economies

Based on the base case with $\rho = 0$, Figure 5.2c shows that the innovation threshold z_t^* grows with the extent of the scope economies, i.e. with parameter ρ. Thus, the *platform launch* is delayed. Note that this ignores potential reductions in development time for the platform's products and is solely caused by the reduction of development costs: Due to the reduction of the regular total development costs by ρ, also the costs for expedited development are reduced, making H_t (i.e. waiting) more attractive. Hence, increased scope economies delay the *platform launch* and allow the manufacturer to wait longer for new innovations. Looking at this from a practitioner's angle, ρ can be understood as a reduction of the size of the individual development projects: Expediting smaller development projects is less costly than expediting larger development projects due to easier coordination, communication, etc.

Innovation sensitivity of the demand

Figure 5.2d shows the change in the threshold, when the demand growth rate of the high-end product, ξ_1, is varied by ± 0.2 of the base case setting ($\xi_1 = 0.5$). We observe that the innovation threshold z_t^* increases in ξ_1. Thus, the *platform launch* is delayed, if the high-end product is more sensitive to technological innovations. Raising ξ_1 increases the expected level of demand for the high-end product; thus, H_t (i.e. waiting) becomes more valuable. The same behavior would be observed, if we keep ξ_1 constant and raise ξ_2 instead.

Time sensitivity of the development costs

Figure 5.2e illustrates the behavior of the threshold, when the development costs growth rate α is varied by ± 0.2 of the base case ($\alpha = 1.5$). The innovation threshold z_t^* is decreasing in α. Thus, if the development costs are more sensitive to reductions in the development time of the new products, the *platform launch* is expedited. The reason is a reduced value of H_t (i.e. waiting), as postponing the *platform launch* by one period becomes more costly.

Number of products

Figure 5.2f shows the impact of adding another product to the platform. In this experiment we use the case $|M'| = 3$ as described in Section 5.5.1 with SOP schedules having varying SOP offsets of 0, 1, or 2 periods between the SOPs, i.e. having simultaneous

SOPs or an offset of one or two periods. The graph shows the cases of simultaneous SOPs (offset of 0), the case of sequential schedule $(\Delta\tau_2, \Delta\tau_3) = (2, 1)$ as an example of an offset of 1, and the case of sequential schedule $(\Delta\tau_2, \Delta\tau_3) = (4, 2)$ as an example of an offset of 2. We observe that the innovation threshold z_t^* is lowered by adding the third product in the base case with simultaneous SOPs.

However, recall that product $m = 3$ is positioned in a segment between the high-end and the low-end products. Therefore, the share of demand generated by the high-end product is reduced and its importance is diminished. As product $m = 3$ is less sensitive to innovation, z_t^* is reduced, leading to an expedited *platform launch*. However, if product $m = 3$ is positioned above $m = 1$, the opposite behavior would be observed. Furthermore, comparing the two sequential SOP schedules to the equivalent schedules (same offset) in Figure 5.2a, z_t^* is slightly raised as a consequence of the increased average residual development time due to the late SOP of product $m = 3$. Therefore, we can conclude that adding a product to the platform can have a significant impact on z_t^*, depending on the product placement and SOP schedule.

Based on the findings presented in this section, we observe that the innovation threshold z_t^* characterizing the optimal *platform launch* policy is sensitive to multiple factors. The manufacturer has to consider the extent of these factors, when deciding on the *platform launch*. Otherwise, the platform might be launched too early, which would reduce the manufacturer's flexibility in incorporating new innovations into the platform, or it might be launched too late, putting too much pressure on the product development projects.

5.5.3. Loss of flexibility due to the use of platforms

It is common knowledge that the standardization established by a product platform influences the customer's perception of the product and therefore can cause losses. So far, this has been discussed in relation to product differentiation: Common design variables of the platform cause a loss of diversification. We investigate another effect, the *loss of flexibility* due to platforms. We note that the loss of flexibility is driven by time ("when to release the platform") compared to the loss of diversification, which is driven by design.

Recall that a platform provides the technological basis for several products. However, at the same time, customers of the technology-based products differ in their sensitivity to innovations. In a platform setup a manufacturer has to compromise between a timely *platform launch* and more innovative products. While waiting is beneficial for the high-

end product to incorporate the latest innovation, it compresses the development time for the low-end product without any benefit.

The compromise of the *platform launch* results in an increase in costs or lost sales compared to the non-platform case, in which the level of innovation can be tailored to each product. This *loss of flexibility* has to be considered in addition to the usual benefits and drawbacks of platforms in order to understand the total impact. In the following analysis, we include the benefits of scale economies and scope economies.

For the purpose of our analysis we define the *platform impact* as

$$PI(\epsilon, \rho) = \frac{V_0^P(\epsilon, \rho) - \sum_{m \in M} V_{0m}^M(\epsilon)}{\sum_{m \in M} V_{0m}^M(\epsilon)} = \frac{V_0^P(\epsilon, \rho)}{\sum_{m \in M} V_{0m}^M(\epsilon)} - 1. \qquad (5.16)$$

V_0^P is the value function in period 0 ($z_0 = 1$) based on the platform approach; V_{0m}^M is the value function of product m in period 0 based on the non-platform approach, assuming product-specific launches of the individual development projects, without joint level of innovation. Both V_0^P and V_{0m}^M are based on the model described in Section 5.3. For V_{0m}^M the model is applied separately for each product.

The *platform impact PI* includes both the *loss of flexibility* and the platform benefits, depending on the setting of parameters ϵ (scale economies) and ρ (scope economies). We define the *loss of flexibility* due to platforms as the *platform impact* of the base case, $PI(0,0)$, in which no platform benefits apply. For $\epsilon > 0$ ($\rho > 0$), the scale economies (scope economies) diminish the *loss of flexibility* and increase the *platform impact*. Note that V_{0m}^M is influenced by ϵ, as scale economies apply to a limited extent (for each product based on the cumulative product volume instead of the platform volume), while it is not influenced by ρ, as each product is developed independently.

Loss of flexibility vs. benefits of platforms

Figure 5.3 illustrates the impact of platforms $PI(\epsilon, \rho)$. For the base case without scale and scope economies (a), the *platform impact PI*(0,0) is -13.5%. Thus, the manufacturer has a *loss of flexibility* of 13.5% of the expected profit of the non-platform case as a consequence of using a shared platform. We note that for the base case the *platform impact* is always lower or equal to 0.

Observation 5.2. *There is a loss of flexibility associated with platforms for heterogeneous products; it originates from the compromise in the level of innovation made at the platform launch.*
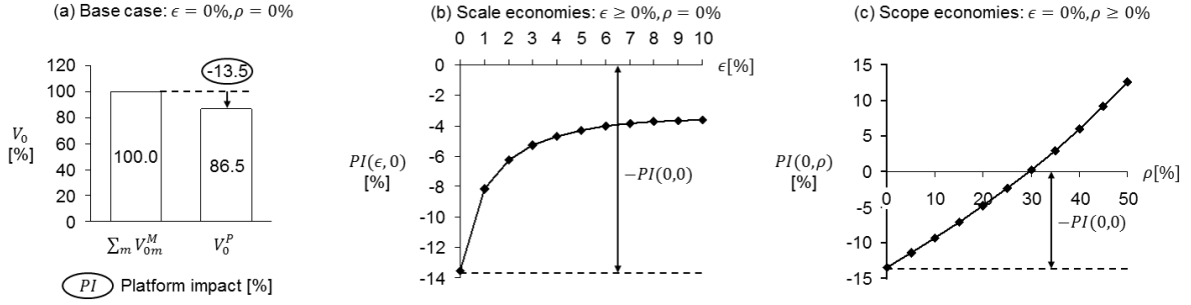
Figure 5.3: Platform impact for (a) the base case, (b) varying scale economies, and (c) varying scope economies.

For the case of scale economies (b), the *platform impact* grows from $PI(0,0)$ with the extent of the scale economies (ϵ); thus, the flexibility loss is partly offset. Nevertheless, PI shows an asymptotic behavior in ϵ, which is caused by the diminishing unit cost reduction for large volumes. Thus, we observe a negative value of PI for the domain of ϵ investigated, i.e. with only scale economies the platform is not beneficial for the manufacturer. We note that the maximum learning parameter of 10% in our experiment corresponds to a 7% drop of the platform-related unit costs, when the cumulative platform volume is doubled. In industries like the automotive sector this drop typically ranges between 3% to 5%. For the case of scope economies (c) the *platform impact* $PI(0,\rho)$ shows an almost linear behavior in ρ and offsets the *loss of flexibility* when $\rho = 30\%$.

Observation 5.3. *Scale economies alone cannot compensate for the loss of flexibility due to platforms. In addition, scope economies must be realized, in order to achieve a positive platform impact.*

SOP sequence matters

The SOP sequence of products with different level of profitability is a critical issue in platform planning. It has been studied in the academic platform planning literature resulting in the perception that introducing the high-end product prior to the low-end product is beneficial in order to prevent cannibalization: Some customers of the high-end segment could buy the low-end product, if it were available first (Krishnan and Gupta, 2001). However, these results ignore the *loss of flexibility* due to platforms.

Therefore, we compare the five SOP schedules $\Delta\tau \in \{-2, -1, 0, 1, 2\}$, i.e. ranging from "low-end product first" with an offset of 2 periods to "high-end product first" with
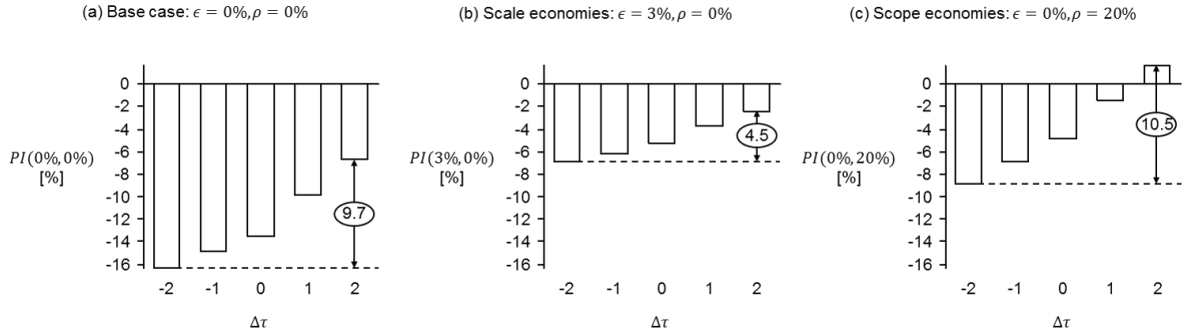
Figure 5.4: Platform impact for varying SOP schedules.

an offset of 2 periods, with respect to the *platform impact* $PI(\epsilon, \rho)$. Based on Figure 5.4 the following observations can be made:

Observation 5.4. *The platform impact PI grows in $\Delta\tau$ and shows the following characteristics:*

1. *PI grows stronger for $\Delta\tau > 0$;*

2. *The influence of $\Delta\tau$ is reduced by scale economies;*

3. *The influence of $\Delta\tau$ is increased by scope economies.*

These observations have several implications. First, we conclude that the *loss of flexibility* due to platforms is less significant for SOP schedules with decreasing profitability ("high-end product first"). This finding extends the findings in the existing literature stating that the high-end product should be introduced prior to the low-end product to the case of an exogenous technology development process considering flexibility losses. Furthermore it shows that such a schedule outperforms a schedule with simultaneous SOPs.

Therefore, if a manufacturer can affect the SOP schedule, the sequence with decreasing profitability should be selected. If the schedule is fixed, e.g. driven by the market or by the SOPs of competitor products, the manufacturer must consider the differences in the *loss of flexibility* when assigning the products to the platforms. For example, if a high-end product is scheduled for a late SOP, a reassignment to another platform could be considered in order to reduce the *loss of flexibility* and improve the platform's impact.

Second, we conclude that the structure of the platform benefits is important. If the savings are driven by scale economies, the SOP sequence matters less; however, if the savings are driven by scope economies, it becomes more important to have a sequence

with decreasing profitability of the platform products. Delaying the *platform launch* becomes less costly in such a setting, which has a stronger impact on the scenarios with $\Delta\tau > 0$. Thus, by prioritizing the implementation of scale effects, the manufacturer can diminish the influence of the SOP schedule on the *platform impact*.

Demand and innovation

Our approach captures the dependency of the product demand on the employed level of innovation based on the demand magnitude η_m and the growth rate ξ_m. As described in Section 5.3.1, η_m corresponds to the size of the base market, i.e. customers accepting basic functionality, and ξ_m characterizes the sensitivity in the segment to the level of innovation. Low-end products are typically characterized by a large base market with little growth in demand for an increasing level of innovation, while high-end products have a small base market and are very sensitive to technological improvements.

In this section we discuss, how these demand characteristics influence the *platform impact* and the associated *loss of flexibility*. Therefore, we analyze the *platform impact PI* for different types of demand behavior described by $\frac{\eta_1}{\eta_2}$ and $\Delta\xi = \xi_1 - \xi_2$. $\frac{\eta_1}{\eta_2} \in [0,1]$ is the demand magnitudes ratio of the high-end to the low-end product. $\Delta\xi = \xi_1 - \xi_2 \in [0,1]$ is the difference in growth between the high-end and the low-end product. A large value of $\Delta\xi$ implies that the high-end product is much more sensitive to technological innovations compared to the low-end product, i.e. the products are heterogeneous.

The results on the influence of the demand behavior are shown in Figure 5.5. $\frac{\eta_1}{\eta_2}$ is varied between 0.1 and 1.0 by letting η_1 approach η_2. $\Delta\xi$ is varied between 0 and 1 by starting at $\xi_1 = \xi_2 = 0.5$ and stepwise increasing the gap toward $\xi_1 = 1$ and $\xi_2 = 0$. The following behavior can be observed:

Observation 5.5. *The platform impact PI and the associated loss of flexibility depend on the magnitudes ratio $\frac{\eta_1}{\eta_2}$ and the difference in growth $\Delta\xi$ of the demand:*

1. *The loss of flexibility decreases with the demand magnitudes ratio $\frac{\eta_1}{\eta_2}$;*

2. *The loss of flexibility increases with the difference in growth $\Delta\xi$;*

3. *Scale economies reduce the influence of an increasing $\Delta\xi$, if both products are sensitive to the level of innovation and $\Delta\xi$ is moderate.*

Therefore, manufacturers should be aware of the market conditions. If the market segments covered by the platform are different in base market size or if customers de-
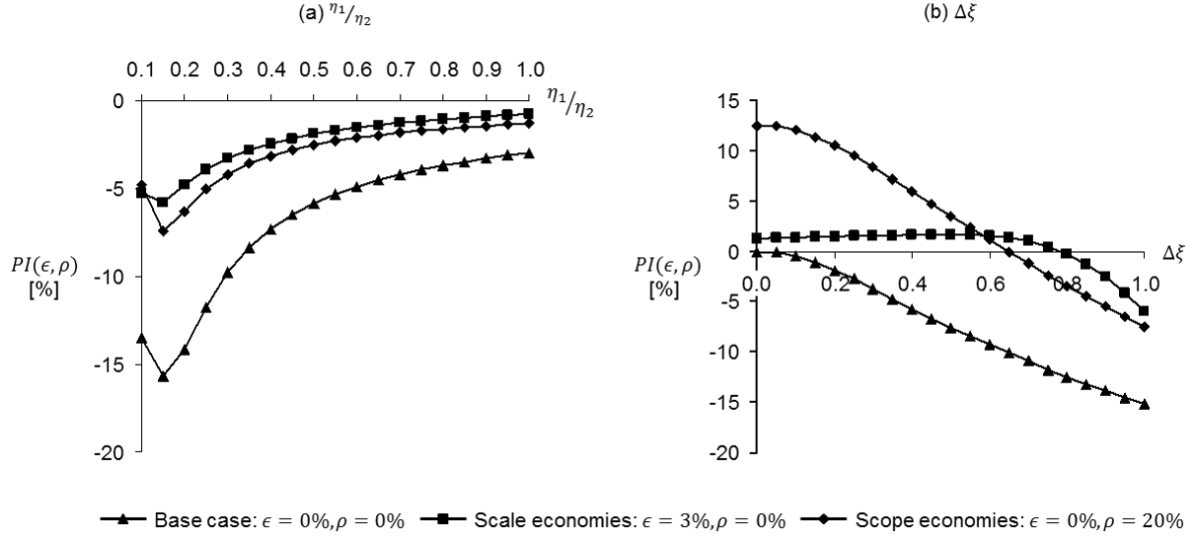
Figure 5.5: Platform impact for varying (a) magnitude ratio and (b) difference in growth.

mand heterogeneous products, it might be beneficial to reassign products to platforms or introduce an additional platform in order to prevent a high *loss of flexibility*.

The influence of $\frac{\eta_1}{\eta_2}$ on PI shown in Figure 5.5a can be explained as follows: As $\xi_2 = 0$, by increasing $\frac{\eta_1}{\eta_2}$ the high-end product has a higher share in the total volume and a stronger impact on the total profits. Thus, the optimal *platform launch* timing is delayed and moves closer to the timing of the individual launch of the high-end product in the non-platform approach. The reduction of the *loss of flexibility* due to the platform cost benefits is independent from $\frac{\eta_1}{\eta_2}$.

We observe in Figure 5.5b that the *loss of flexibility* increases with $\Delta\xi$, caused by either increased lost sales or increased development costs compared to the non-platform approach. The effect of scope economies is almost independent from $\Delta\xi$. However, the influence of scale economies depends significantly on $\Delta\xi$: For heterogeneous products the scale economies can still balance the increasing *loss of flexibility* up to a heterogeneity of $\Delta\xi = 0.7$; for products with stronger heterogeneity, however, the increase in lost sales cannot be compensated anymore. Therefore, we can conclude that scale economies are more efficient for less heterogeneous products. In summary, we can state that especially for products strongly differing in the base customer amount or the sensitivity to innovation, the *loss of flexibility* is very high.

Linking the loss of flexibility to the multi-platform strategy

In this section we link the *loss of flexibility* caused by the *platform launch* to the product-to-platform assignment in multi-platform strategies. Therefore, we use the case of $M' = \{1, 2, 3\}$ with a low-end (L), high-end (H), and intermediate (I) product as defined in Section 5.5.1.

For selected SOP schedules with an SOP offset of 2 periods, the case of a single platform, denoted as "HIL", is compared against the case of two platforms with different product-to-platform assignments, denoted by "HL+I", "HI+L", and "IL+H". For example, "HL+I" refers to the case of a platform shared by the high-end and the low-end products, while the intermediate product is assigned to a second platform. Note that this notation only describes the product-to-platform assignment and is not associated with the SOP timing.

For the purpose of this analysis, the definition of the *platform impact PI* in (5.16) is modified to

$$PI(\epsilon, \rho) = \frac{V_0^P(\epsilon, \rho) + V_{0m'}^M(\epsilon)}{\sum_{m \in M} V_{0m}^M(\epsilon)} - 1, \tag{5.17}$$

where $V_{0m'}^M$ is the value function of the product m' that is assigned to a separate platform. Table 5.3 shows the *loss of flexibility* $(PI(0,0))$ for the SOP schedules $\Delta\tau = (\Delta\tau_2, \Delta\tau_3) = (-4, -2), (-2, 2), (4, 2)$:

Observation 5.6. *The loss of flexibility due to platforms strongly depends on the product-to-platform assignment in a multi-platform strategy:*

1. *The influence of the product-to-platform assignment is smallest for SOP schedules with decreasing product profitability.*

2. *The loss of flexibility increases in the number of products assigned to the platform and decreases in the number of platforms.*

3. *The influence of the product-to-platform assignment and the number of platforms varies significantly depending on the SOP schedule.*

For some SOP schedules, the *loss of flexibility* can be drastically reduced by introducing an additional platform and, therefore, reducing the number of products per platform. In our experiment this is the case for the "HI+L" assignment (in any schedule). However, increasing the number of platforms does not need to reduce the *loss of flexibility* to a significant extent, as can be observed for the case of the "HL+I" assignment. In all three cases the additional platform for the intermediate product marginally reduces the

Table 5.3: Loss of flexibility for varying product-to-platform assignments.

| $\Delta\tau$ | $PI(0\%, 0\%)$ | | | |
	HIL	HL+I	HI+L	IL+H
(4,2)	-1.32%	-1.31%	-0.46%	-0.22%
(2,4)	-5.02%	-3.70%	-0.06%	-3.95%
(-4,-2)	-12.52%	-12.51%	-2.36%	-4.59%

flexibility loss. Furthermore, there are cases, for which the influence of the additional platform strongly depends on the SOP schedule. For example, the case of the "IL+H" assignment almost eliminates the *loss of flexibility* for the schedule $\Delta\tau = (4,2)$ with decreasing profitability, while it has just a limited influence for the schedule $\Delta\tau = (2,4)$.

Therefore, a careful consideration of the *loss of flexibility* that is sensitive to the SOP schedule is necessary, when a manufacturer assigns products to platforms in a multi-platform strategy. For the case of the MRA platform of *Mercedes-Benz*, the SOP schedule was similar to the schedule $\Delta\tau = (2,4)$. We observe that in this case the *loss of flexibility* could have been eliminated by adjusting the product-to-platform allocation to "HI+L", i.e. by excluding the low-end product from the platform.

5.6. Conclusion

In this chapter we introduced the problem of *dynamic platform planning* for technology-based products. A manufacturer employing a platform strategy has to decide, when to release a platform for the individual product development. The timing of the *platform launch* is critical. Individual product development projects cannot be initiated prior to the *platform launch*. However, technological innovations cannot be incorporated into the platform after the *platform launch*. The uncertainty of the success and the completion timing of the exogenous R&D projects increase the complexity of the planning problem.

Based on a stylized optimization model for *dynamic platform planning*, assuming a stochastic innovation process, we find that the optimal policy for the *platform launch* is described by a time-dependent threshold for the level of technological innovation. Furthermore, we identify a disadvantage of platforms originating from the compromise in timing and innovation level set by the *platform launch*, denoted as *loss of flexibility*. The *loss of flexibility* reduces the well-known platform benefits and extends the concept of loss of diversification, as it is driven by time ("when to release the platform?").

Based on the example of the MRA platform of *Mercedes-Benz*, we have four key

findings in our numerical experiments. First, scale economies related to platforms alone cannot compensate for the *loss of flexibility*; scope economies are required on top to achieve a positive impact. Second, the extent of the *loss of flexibility* depends on the SOP schedule and is lowest for a "high profit first" schedule. Third, the *loss of flexibility* increases, if the products sharing the platform are very heterogeneous. Fourth, the product-to-platform assignment has significant impact on the *loss of flexibility*; thus, the *loss of flexibility* must be carefully considered in the context of the given SOP schedule, already when the manufacturer assigns products to platforms.

We note that the platform benefits implemented in our experiments are limited to scale economies and scope economies in manufacturing, development, and other processes. We do not consider other platform benefits, such as effects on the development and ramp-up time as well as other non-monetary benefits of standardization. However, the concept of *loss of flexibility* still applies, if additional platform benefits are included. Furthermore, the implemented scale and scope economies reflect a large share of the benefits of platforms.

Future research could focus on integrating *dynamic platform planning* with other planning problems such as the product-to-platform assignment and the planning of SOPs. Such integration would ensure that the *loss of flexibility* is considered already at higher planning levels, facilitating a high total platform benefit.

Furthermore, we only consider the uncertainty in the exogenous R&D process supplying the technological innovations. Future research could analyze other sources of uncertainty in *dynamic platform planning*, such as the uncertainties related to technology diffusion in the market and the customer acceptance of new product concepts (e.g. for alternative powertrains in cars).

We currently observe in industrial practice that many manufacturers ignore the *loss of flexibility*, despite its large impact. For the *Mercedes-Benz* MRA platform, we observe that the *loss of flexibility* is not at its minimum, as the SOP sequence is not decreasing in profitability. It could be reduced by adjusting the product-to-platform assignment or the SOP schedule (if possible).

Furthermore, in order to obtain a positive impact of a platform, manufacturers must ensure that the intended platform benefits do materialize. Processes must be adapted such that the scale and scope economies are facilitated. Therefore, company-wide restructuring that reflects the selected product-to-platform assignment must be implemented. However, many manufacturers that introduced product platforms keep their traditional organizational structure, e.g. based on products or regions, causing the plat-

form strategy to fail.

Chapter 6.

Conclusion

This chapter provides a summary of the research presented in the previous chapters and discusses the findings with regard to the research questions and the comprehensive research objective defined in Section 1.2. Furthermore, the resulting directions for future research are discussed.

6.1. Summary

Current industry developments cause a challenging environment for automotive manufacturers. Mitigation strategies, such as product platforms and modularization, are in place, however, require an increased degree of integration in planning processes and optimization tools. In particular, the integration of cyclic planning processes with design projects is challenging. Therefore, this thesis aimed at supporting automotive manufacturers in this transition by focusing on three research topics, defined by distinct research questions. The research topics were selected to provide contributions to both fields, the research on planning processes at automotive manufacturers and the research on optimization approaches to support these processes, and to bridge between academic research and industrial practice.

In the following, we first summarize the findings with respect to each of the three research topics and provide a comprehensive conclusion at the end of the section.

Research Question 1.A. *How should the process for integrated business planning be defined for automotive manufacturers to systematically integrate cyclic planning with the planning of design projects? What are the challenges in integrated business planning and what is the state of the art in the industry?*

Chapter 2 focused on processes for integrated business planning in the automotive

industry. A reference process for integrated business planning at automotive manufacturers was presented. The reference process synthesizes data collected during several industry interviews and data found in academic literature. It integrates the cyclic planning processes with the planning processes of design projects. Based on this reference process, integration challenges for automotive OEMs were identified based on a novel classification scheme. The scheme distinguishes two types of challenges, challenges related to design projects diverging from strategic cyclic processes and challenges related to design projects converging into tactical cyclic processes. The strategic cyclic processes for platform planning, module planning, and long-term demand planning define the strategy of the OEM and converge into design projects aiming at the implementation of the strategy. There are three types of design projects: new vehicle design, strategic (production and sourcing) network design, and process technology design. The projects typically have a duration of several years and finally converge into the tactical S&OP process.

To secure a systematic integration of the cyclic planning processes with the processes for design projects, mechanisms are required to coordinate these integration challenges. The mechanisms must structure the flow of information despite differences in planning modes, horizons, and frequencies, enable cross-functional and cross-product alignment, and guarantee comprehensive optimization.

To address Research Question 1.A, a thorough analysis of the current industry practice was conducted. We found a total of six distinct integration challenges, three challenges based on divergence and three challenges based on convergence. For the design projects diverging from strategic cyclic processes, the systematic coordination requires mechanisms sensitive to the different planning modes, i.e. multi-year projects versus annual planning cycles, to the diverse SOPs of car models, and to the interdependencies between products and common modules. Manufactures currently use freezing mechanisms that reduce the complexity of the coordination, however also reduce the decision flexibility. To coordinate the new vehicle design and strategic network design projects diverging from platform planning and from module planning, freezing mechanisms termed "platform launch" and "module fixing" are used. To coordinate capacity planning projects diverging from strategic volume planning, manufacturers freeze the central forecast ("capacity fixing") two years before the earliest associated SOP. For all three challenges, functional biases in the cross-functional teams were discovered. Furthermore, we found a lack of integration of platform planning with process technology design projects.

The systematic coordination of the strategic network design projects converging into

the S&OP process has become important, as the planning for current and for future products must be constantly aligned in the context of product platforms, modularization, and frequent ramp-ups. The three challenges associated with this alignment are the convergence of production network design projects into annual BP, the convergence of sourcing network design projects into annual CSP, and the convergence of tactical ramp-up planning projects into monthly *MPP*. For all three challenges, no firmly established coordination mechanism could be identified in industrial practice. As a result, we found a severe lack of transparency and alignment at automotive OEMs, partly caused by the organizations and the IT systems being disconnected across the planning landscapes.

Research Question 1.B. *To what extent do optimization approaches proposed in academic literature support integrated business planning and the corresponding integration challenges? What are the resulting priorities for future academic research?*

In Chapter 3, we focused on optimization approaches supporting integrated business planning in the automotive industry. Based on the reference process and the integration challenges defined in Chapter 2, a comprehensive review of 69 OR approaches was presented. The review focuses on four selected integration challenges: (i) diverging cyclic platform planning into design projects, (ii) diverging cyclic strategic volume planning into network design projects, (iii) converging network design projects into the cyclic S&OP process, and (iv) converging tactical ramp-up planning projects into cyclic S&OP.

Based on classification criteria defined for each challenge, a detailed analysis of the state-of-the-art literature was conducted to address Research Question 1.B. In summary, even though there is also innovative work, it can be concluded that academic literature shows similar shortcomings as industrial practice. Existing research has been focused on standard problems in individual processes, mostly ignoring cross-functional interdependencies. For example, future research should focus on optimization approaches supporting the integration of design projects into platform planning or on optimization approaches considering demand flexibility instruments to facilitate cross-functional interaction for the diverging of capacity planning projects from strategic volume planning. Furthermore, existing research disregards the different characteristics of project planning and cyclic planning.

Research Question 2. *How can interdependencies between the cyclic forecasting process and the capacity planning projects be systematically addressed? To what extent can*

investment risk be considered in the time-phased decision making? What is the impact of an early central capacity fixing and of flexible body shops enabled by modularization?

Chapter 4 focused on capacity planning projects at automotive OEMs and the interdependency with the cyclic forecasting process under demand uncertainty. Capacity planning projects are characterized by time-phased investment decisions. The demand forecasting process provides annual volume updates. To address the interdependency and support time-phased capacity planning, we presented an innovative modeling approach based on an MDP. The approach employs transition functions that systematically model the dynamics of time-phased decisions and of cyclic forecasting updates making use of the Bayesian updating concept. To enable decision making sensitive to the risk attitude and to prevent time-inconsistency, the CVaR decomposition theorem was implemented in the dynamic modeling approach, enabled by a novel transition function based on a discretized, variable CVaR level.

We applied the approach to a typical automotive capacity planning problem. It was shown that the developed dynamic optimization approach is superior in the context of time-phased capacity planning compared to the state of the art in stochastic optimization. The benefit of our approach was found to be large in volatile environments and for risk-averse OEMs.

To answer the last part of Research Question 2, the central capacity fixing strategy and the flexible body shops enabled by modularization were studied as part of the numerical experiments. We found that central capacity fixing is an effective mechanism against misaligned capacity configurations of manufacturing stages during time-phased capacity planning. However, it comes at significant costs due to reduced planning flexibility. The reduced planning flexibility is especially costly for risk-averse manufacturers. Furthermore, we found that flexible body shops come at hidden costs that diminish the benefits of capacity pooling. The costs result from a loss of decision flexibility in time-phased decision making, as manufacturers must commit early on to a joint capacity configuration for all considered products.

Research Question 3. *How can the interdependency between the technology innovation projects and the platform planning process be analytically described? Can the optimal policy for the platform launch be characterized by structural properties? Are there considerable flexibility losses due to platforms?*

Chapter 5 focused on dynamic platform planning under uncertain technological innovations. The timing of the platform launch determines the trade-off between the

technology level employed by the platform and the time available for the individual development projects of the derivatives. To describe this interdependency, we developed a stylized optimization model based on an MDP assuming a stochastic innovation process. The model further employs time-sensitive product development costs and innovation-sensitive customer demand to systematically address the trade-off in dynamic platform planning.

Based on the stylized model, it was shown that the optimal policy for the platform launch is characterized by a time-dependent threshold for the level of technological innovation. It was further shown that the threshold decreases as the platform planning process evolves over time approaching the SOPs of the derivatives.

We applied the developed modeling approach for a typical automotive platform planning setting. We found a significant disadvantage of platforms, termed loss of flexibility. It results from the trade-off made when deciding on the timing of the platform launch. The loss of flexibility extends the concept of loss of diversification and can significantly reduce the platform benefits. In our numerical experiment, for example, scale economies resulting from the platform alone could not compensate for the loss of flexibility. Furthermore, the loss of flexibility depends on the SOP schedule, on the product heterogeneity of the derivatives, and on the product-to-platform assignment. Despite its significance, automotive manufacturers have so far ignored the loss of flexibility, as can be seen by the industry example used in our numerical experiments.

In summary, this thesis aimed at supporting automotive manufacturers in the transition to integrated planning in the context of product platforms and modularization. With respect to this objective, several comprehensive findings can be made.

First, we can conclude that, from the perspective of both industrial practice and academic research, the state of integrated planning is more advanced for the integration challenges related to design projects diverging from strategic cyclic processes than for the challenges related to design projects converging into S&OP. In industrial practice, for all three challenges related to divergence, coordination mechanisms could be identified. Furthermore, by developing two optimization approaches, we provided methodologies that are designed according to the characteristics required for this type of integration.

Second, we found that the mechanisms employed by automotive OEMs to coordinate the interaction between a strategic cyclic process and the design projects, implement fixing strategies and aim at reducing the manufacturer's risk. We showed that the fixing strategies cause a performance loss for the manufacturer due to the reduced decision

flexibility. Furthermore, fixing strategies do not reduce the risk, but lead to an increased performance loss, when risk preferences are considered in decision making. Based on the two developed optimization approaches, we showed that dynamic approaches are better suited in this context. Both methodologies can serve as prototypes for optimization approaches that aim at supporting other integration challenges.

Third, besides the well-known benefits, product platforms and vehicle modularization also cause disadvantages. The application of both optimization approaches showed that flexibility in planning is sacrificed due to the increased interdependency between the planning processes. Reduced planning flexibility implies reduced responsiveness in planning and, on average, causes a performance loss. In general, the loss was found to be particularly high for cases with diverse SOPs of the associated products. This finding is of high relevance for automotive manufacturers, as diverse SOPs are common industry practice.

Finally, the research on planning processes and optimization approaches presented in this thesis originates from the context of the automotive industry. However, the challenges of integrated business planning as well as the underlying dynamics of the decision problems investigated are not limited to the automotive industry. Similar challenges and decision problems can be found in other industrial settings. Therefore, the reference process, the integration challenges, and the developed optimization approaches for time-phased capacity planning and dynamic platform planning are applicable in other industries, for example process industries or other manufacturing industries.

6.2. Directions for future research

Based on the research presented in this thesis, several opportunities for future research on both planning processes at automotive manufacturers and related optimization approaches arise. In the following, we present comprehensive research directions that build a synthesis of the findings and research opportunities identified for each of the three research topics.

It is important that future research focuses on broadening the academic perspective on integrated business planning, as it is a young field offering many gaps. Building on the reference process defined in Chapter 2 and the detailed analysis of the two selected challenges in Chapters 4 and 5, other integration challenges could be analyzed in detail. Especially the challenges related to design projects converging into the S&OP process deserve a detailed analysis and should be aimed at by future optimization approaches.

Furthermore, future research could focus on integrated business planning in the context of other industries or on other aspects of integrated business planning, for example related to the IT infrastructure or the design of functional incentives in associated coordination mechanisms.

Common platforms and common modules typically cause additional, temporal synergies. As the discussion in Chapters 2 and 3 has shown, it is important to consider the temporal synergies in integrated business planning. For example, for the challenge related to design projects diverging from platform planning, the platform planning process has an impact on the time-to-market of each derivative. As platforms can significantly reduce the product development time, there is an interdependency between the platform strategy (allocation and timing) and the planning of new product development projects. Thus, future research could focus on analyzing this interdependency, for example by integrating the planning of SOPs with the dynamic platform planning problem, building on the model presented in Chapter 5.

Based on our findings, product platforms and modularization cause a loss of decision flexibility diminishing the benefits, especially in industries as the automotive sector, in which SOPs of products are typically diverse. Thus, building on the optimization approaches presented in this thesis, future research could develop approaches aiming at minimizing this loss. In time-phased capacity planning, for example, approaches could be developed to determine the body shop layout. A shared body shop could be used for some derivatives, while for other derivatives a dedicated body shop is beneficial due to the increased flexibility for the capacity decision. Furthermore, in platform planning, approaches could be developed that consider the loss of flexibility due to platforms on a higher planning level, for example by integrating the product-to-platform assignment with the dynamic platform planning problem.

As shown by the discussion in Chapter 3, due to the high degree of interdependency, it is important to consider the uncertainties resulting from internal planning processes in integrated business planning. Therefore, future research could focus on extending the analysis on internal uncertainties. For example, our research on time-phased capacity planning focused on the uncertainty resulting from the forecasting process. It could be extended to consider uncertainties of supplier lead times and construction times or the uncertainty of the availability of new production technologies. One option could be to introduce a similar methodology as we developed it for the stochastic R&D process in the dynamic platform planning problem.

Finally, as the reference process presented in Chapter 2 has shown, integrated busi-

ness planning in the context of product platforms and modularization is very complex due to the high degree of interdependency and connectedness. Therefore, to successfully accomplish the transition to integrated business planning, it will be important for manufacturers to determine the appropriate degree of integration for each integration challenge and select the data points required for efficient planning and optimization. Going forward, in the age of digitization and big data, the amount of data available as well as the capabilities of IT-tools and the computational power will grow fast and enable a higher degree of integration. Thus, it will be challenging to find the right balance between enhancing the level of granularity and maintaining stable processes. However, many research questions that cannot be answered today will become solvable. Hence, it will be important for practitioners and researchers to consistently challenge the state of the art in integrated planning and optimization.

Bibliography

AlGeddawy, T. and H. ElMaraghy (2013). Reactive design methodology for product family platforms, modularity and parts integration. *CIRP Journal of Manufacturing Science and Technology* **6**(1), pp. 34–43.

Aoki, K. and T. Stäblein (2017). Monozukuri capability and dynamic product variety: An analysis of the design-manufacturing interface at Japanese and German automakers. *Technovation*.

Askar, G. (2008). Optimierte Flexibilitätsnutzung in Automobilwerken. Aachen: Shaker.

Askar, G., T. Sillekens, L. Suhl, and J. Zimmermann (2007). Flexibility planning in automotive plants. In: *Management logistischer Netzwerke: Entscheidungsunterstützung, Informationssysteme und OR-Tools.* Ed. by H.-O. Günther, D. C. Mattfeld, and L. Suhl. Heidelberg: Physica, pp. 235–255.

Azoury, K. S. (1985). Bayes solution to dynamic inventory models under unknown demand distribution. *Management Science* **31**(9), pp. 1150–1160.

Bartnik, R., T. Stäblein, and K. Aoki (2016). How does firm context influence automotive order fulfilment? A structured review of current knowledge. Paper presented at: *Nineteenth International Working Seminar on Production Economics.* Feb. 22-26, 2016. Innsbruck.

Bean, J. C., J. L. Higle, and R. L. Smith (1992). Capacity expansion under stochastic demands. *Operations Research* **40**(3), pp. 210–216.

Becker, A., R. Stolletz, and T. Stäblein (2017). Strategic ramp-up planning in automotive production networks. *International Journal of Production Research* **55**(1), pp. 59–78.

Ben-Arieh, D., T. Easton, and A. M. Choubey (2009). Solving the multiple platforms configuration problem. *International Journal of Production Research* **47**(7), pp. 1969–1988.

Bhandare, S. and V. Allada (2009). Scalable product family design: Case study of axial piston pumps. *International Journal of Production Research* **47**(3), pp. 585–620.

Bibliography

Bihlmaier, R., A. Koberstein, and R. Obst (2009). Modeling and optimizing of strategic and tactical production planning in the automotive industry under uncertainty. *OR Spectrum* **31**(2), pp. 311–336.

Biller, S. and J. Swann (2006). Pricing for environmental compliance in the auto industry. *Interfaces* **36**(2), pp. 118–125.

Biller, S., L. M. A. Chan, D. Simchi-Levi, and J. Swann (2005). Dynamic pricing and the direct-to-customer model in the automotive industry. *Electronic Commerce Research* **5**(2), pp. 309–334.

Boas, R., B. G. Cameron, and E. F. Crawley (2013). Divergence and lifecycle offsets in product families with commonality. *Systems Engineering* **16**(2), pp. 175–192.

Boda, K. and J. A. Filar (2006). Time consistent dynamic risk measures. *Mathematical Methods of Operations Research* **63**(1), pp. 169–186.

Bornschlegl, M., S. Kreitlein, M. Bregulla, and J. Franke (2015). A method for forecasting the running costs of manufacturing technologies in automotive production during the early planning phase. *Procedia CIRP* **26**, pp. 412–417.

Boyer, K. K. and G. K. Leong (1996). Manufacturing flexibility at the plant level. *Omega* **24**(5), pp. 495–510.

Boysen, N., M. Fliedner, and A. Scholl (2009). Production planning of mixed-model assembly lines: Overview and extensions. *Production Planning & Control* **20**(5), pp. 455–471.

Bundschuh, M. (2008). Modellgestützte strategische Planung von Produktionssystemen in der Automobilindustrie. Hamburg: Verlag Dr. Kovac.

Chandra, C., M. Everson, and J. Grabis (2005). Evaluation of enterprise-level benefits of manufacturing flexibility. *Omega* **33**(1), pp. 17–31.

Chen, C. and L. Wang (2008). Multiple-platform based product family design for mass customization using a modified genetic algorithm. *Journal of Intelligent Manufacturing* **19**(5), pp. 577–589.

Chen, M., Y. Xia, and X. Wang (2010). Managing supply uncertainties through Bayesian information update. *IEEE Transactions on Automation Science and Engineering* **7**(1), pp. 24–36.

Clark, K. B. and T. Fujimoto (1991). Product development performance: Strategy, organization, and management in the world auto industry. Boston: Harvard Business School Press.

Cohen, M. A., J. Eliashberg, and T.-H. Ho (1996). New product development: The performance and time-to-market tradeoff. *Management Science* **42**(2), pp. 173–186.

Cooper, R. G. (2011). Winning at new products: Creating value through innovation. 4th ed. New York: Basic Books.

Cornet, A. (2002). Plattformkonzepte in der Automobilentwicklung. Wiesbaden: Springer.

Daimler (2015). Mercedes-Benz Cars Operations (MO): Transforming production. Accessed at Feb. 28, 2018. URL: `https://www.daimler.com/dokumente/investoren/kapitalmarkttage/daimler-ir-mercedes-benzcarscapitalmarketdaymarkusschaefer-20150611.pdf`.

de Boer, L., E. Labro, and P. Morlacchi (2001). A review of methods supporting supplier selection. *European Journal of Purchasing & Supply Management* **7**(2), pp. 75–89.

de Weck, O. L., E. S. Suh, and D. Chang (2003). Product family and platform portfolio optimization. Paper presented at: *ASME Design Engineering Technical Conferences*. Sept. 2-6, 2003. Chicago.

de Weck, O. L. (2006). Determining product platform extend. In: *Product platform and product family design: Methods and applications.* Ed. by T. W. Simpson, Z. Siddique, and J. Jiao. New York: Springer, pp. 241–301.

Dharmani, S., D. Anand, and M. Demirci (2015). Shifting gear - Capacity management in the automotive industry. Accessed at Feb. 28, 2018. URL: `http://www.ey.com/Publication/vwLUAssets/EY-shifting-gear-capacity-management-in-the-automotive-industry/$FILE/1002043%20SP1600%20Advisory%20Supply%20Chain%20Whitepaper_V15_LR%20pdf%20-%20Updated.pdf`.

Druehl, C. T., G. M. Schmidt, and G. C. Souza (2009). The optimal pace of product updates. *European Journal of Operational Research* **192**(2), pp. 621–633.

ElMaraghy, H. et al. (2013). Product variety management. *CIRP Annals - Manufacturing Technology* **62**(2), pp. 629–652.

Eppen, G. D., R. K. Martin, and L. Schrage (1989). OR practice - A scenario approach to capacity planning. *Operations Research* **37**(4), pp. 517–527.

Ernst & Young (2015a). Integrated business planning: Unlocking business value in uncertain times. Accessed at Feb. 28, 2018. URL: `http://www.ey.com/Publication/vwLUAssets/EY-Integrated-Business-Planning/$FILE/EY-Integrated_Business_Planning.pdf`.

— (2015b). Investitionsboom in der weltweiten Autobranche. Accessed at Feb. 28, 2018. URL: `http://www.ey.com/Publication/vwLUAssetsPI/EY_VDA_-_Investitionsboom_in_der_weltweiten_Autobranche/$FILE/EY-VDA-Studie-Investitionen-Automobilindustrie.pdf`.

Bibliography

Escudero, L. F., E. Galindo, G. García, E. Gómez, and V. Sabau (1999). Schumann, a modeling framework for supply chain management under uncertainty. *European Journal of Operational Research* **119**, pp. 14–34.

Esmaeilikia, M. et al. (2016). Tactical supply chain planning models with inherent flexibility: Definition and review. *Annals of Operations Research* **244**(2), pp. 407–427.

Ferber, S. (2005). Strategische Kapazitäts- und Investitionsplanung in der globalen Supply Chain eines Automobilherstellers. Aachen: Shaker.

Fettke, P. and P. Loos (2003). Classification of reference models: A methodology and its application. *Information Systems and e-Business Management* **1**(1), pp. 35–53.

Fleischmann, B., S. Ferber, and P. Henrich (2006). Strategic planning of BMW's global production network. *Interfaces* **36**(3), pp. 194–208.

Francas, D., M. Kremer, S. Minner, and M. Friese (2009). Strategic process flexibility under lifecycle demand. *International Journal of Production Economics* **121**(2), pp. 427–440.

Francas, D., N. Löhndorf, and S. Minner (2011). Machine and labor flexibility in manufacturing networks. *International Journal of Production Economics* **131**(1).

Friese, M. (2008). Planung von Flexibilitäts- und Kapazitätsstrategien für Produktionsnetzwerke der Automobilindustrie. *Ph.D. thesis*. Garbsen: Gottfried Wilhelm Leibniz Universität Hannover.

Fujita, K. (2002). Product variety optimization under modular architecture. *Computer-Aided Design* **34**(12), pp. 953–965.

Gan, T.-S. and M. Grunow (2016). Concurrent product and supply chain design: A literature review, an exploratory research framework and a process for modularity design. *International Journal of Computer Integrated Manufacturing* **29**(12), pp. 1255–1271.

Garcia-Sabater, J. P., J. Maheut, and J. J. Garcia-Sabater (2011). A two-stage sequential planning scheme for integrated operations planning and scheduling system using MILP: The case of an engine assembler. *Flexible Services and Manufacturing Journal* **24**(2), pp. 171–209.

Germany Trade & Invest (2016). Industry overview: The automotive industry in Germany. Accessed at Feb. 28, 2018. URL: https://www.gtai.de/GTAI/Content/EN/Invest/_SharedDocs/Downloads/GTAI/Industry-overviews/industry-overview-automotive-industry-en.pdf.

Gershenson, J. K., G. J. Prasad, and Y. Zhang (2004). Product modularity: Measures and design methods. *Journal of Engineering Design* **15**(1), pp. 33–51.

Gjerde, K. A. P., S. A. Slotnick, and M. J. Sobel (2002). New product innovation with multiple features and technology constraints. *Management Science* **48**(10), pp. 1268–1284.

Glock, C. H. and E. H. Grosse (2015). Decision support models for production ramp-up: A systematic literature review. *International Journal of Production Research*, pp. 1–15.

Gneiting, P. R. (2009). Supply Chain Design für modulare Fahrzeugarchitekturen. *Ph.D. thesis*. Zürich: Eidgenössische Technische Hochschule Zürich.

Gnoni, M. G., R. Iavagnilio, G. Mossa, G. Mummolo, and A. Di Leva (2003). Production planning of a multi-site manufacturing system by hybrid modelling: A case study from the automotive industry. *International Journal of Production Economics* **85**(2), pp. 251–262.

Gönsch, J., M. Hassler, and R. Schur (2018). Optimizing conditional value-at-risk in dynamic pricing. *OR Spectrum* **40**(3), pp. 711–750.

Gopal, A., M. Goyal, S. Netessine, and M. Reindorp (2013). The impact of new product introduction on plant productivity in the North American automotive industry. *Management Science* **59**(10), pp. 2217–2236.

Graves, S. B. (1989). The time-cost tradeoff in research and development: A review. *Engineering Costs and Production Economics* **16**(1), pp. 1–9.

Graves, S. C. and B. T. Tomlin (2003). Process flexibility in supply chains. *Management Science* **49**(7), p. 907.

Grimson, J. A. and D. F. Pyke (2007). Sales and operations planning: An exploratory study and framework. *The International Journal of Logistics Management* **18**(3), pp. 322–346.

Hab, G. and R. Wagner (2013). Projektmanagement in der Automobilindustrie. 4th ed. Wiesbaden: Springer.

Hahn, C. K., E. A. Duplaga, and J. L. Hartley (2000). Supply-chain synchronization: Lessons from Hyundai Motor Company. *Interfaces* **30**(4), pp. 32–45.

Hanafy, M. and H. ElMaraghy (2014). A modular product multi-platform configuration model. *International Journal of Computer Integrated Manufacturing* **28**(9), pp. 999–1014.

Hemig, C. (2010). Integrierte Produktions- und Personalplanung auf parallelen Produktionslinien in der Automobilindustrie. Aachen: Shaker.

Bibliography

Hemig, C., J. Rieck, and J. Zimmermann (2014). Integrated production and staff planning for heterogeneous, parallel assembly lines: An application in the automotive industry. *International Journal of Production Research* **52**(13), pp. 3966–3985.

Henrich, P. (2002). Strategische Gestaltung von Produktionssystemen in der Automobilindustrie. Aachen: Shaker.

Hollmann, D. (2011). Supply chain network design under uncertainty and risk. *Ph.D. thesis*. Middlesex: Brunel University.

Holweg, M. (2003). The three-day car challenge: Investigating the inhibitors of responsive order fulfilment in new vehicle supply systems. *International Journal of Logistics Research and Applications* **6**(3), pp. 165–183.

Holweg, M. and F. K. Pil (2004). The second century - Reconnecting customer and value chain through build-to-order. The MIT Press. Cambridge: Massachusetts Institute of Technology.

Holweg, M., S. M. Disney, P. Hines, and M. M. Naim (2005). Towards responsive vehicle supply: A simulation-based investigation into automotive scheduling systems. *Journal of Operations Management* **23**(5), pp. 507–530.

Huang, K. and S. Ahmed (2009). The value of multistage stochastic programming in capacity planning under uncertainty. *Operations Research* **57**(4), pp. 893–904.

Inman, R. R. and D. J. A. Gonsalvez (2001). A mass production product-to-plant allocation problem. *Computers & Industrial Engineering* **39**, pp. 255–271.

Iyengar, G. N. (2005). Robust dynamic programming. *Mathematics of Operations Research* **30**(2), pp. 257–280.

Jana, P. and M. Grunow (2018a). Integrated business planning in the automotive industry: Reference process and literature review. *Submitted for publication.*

— (2018b). Time-phased capacity planning in the automotive industry. *Submitted for publication.*

Jana, P., S. C. Graves, and M. Grunow (2018). Balancing benefits and flexibility losses in platform planning. *Submitted for publication.*

Jiao, J. and Y. Zhang (2005). Product portfolio planning with customer-engineering interaction. *IIE Transactions* **37**(9), pp. 801–814.

Jiao, J., T. W. Simpson, and Z. Siddique (2007). Product family design and platform-based product development: A state-of-the-art review. *Journal of Intelligent Manufacturing* **18**(1), pp. 5–29.

Jordan, W. C. and S. C. Graves (1995). Principles on the benefits of manufacturing process flexibility. *Management Science* **41**(4), pp. 577–594.

KPMG (2014). Strategic integrated business planning. Accessed at Feb. 28, 2018. URL: `http://www.kpmg-institutes.com/content/dam/kpmg/advisory-institute/pd` `f/2013/strategic-integrated-business-planning.pdf`.

Kabak, O. and F. Ülengin (2011). Possibilistic linear-programming approach for supply chain networking decisions. *European Journal of Operational Research* **209**(3), pp. 253–264.

Kaminsky, P. and M. Yuen (2014). Production capacity investment with data updates. *IIE Transactions* **46**(7), pp. 664–682.

Kang, C. M., Y. S. Hong, and W. T. Huh (2012). Platform replacement planning for management of product family obsolescence. *IIE Transactions* **44**(12), pp. 1115–1131.

Kauder, S. (2008). Strategische Planung internationaler Produktionsnetzwerke in der Automobilindustrie. *Ph.D. thesis*. Wien: Wirtschaftsuniversität Wien.

Kauder, S. and H. Meyr (2009). Strategic network planning for an international automotive manufacturer. *OR Spectrum* **31**(3), pp. 507–532.

Ke, T. T., Z.-J. M. Shen, and S. Li (2013). How inventory cost influences introduction timing of product line extensions. *Production and Operations Management* **22**(5), pp. 1214–1231.

Kirshner, S. N., Y. Levin, and M. Nediak (2017). Product upgrades with stochastic technology advancement, product failure, and brand commitment. *Production and Operations Management* **26**(4), pp. 742–756.

Koberstein, A., E. Lukas, and M. Naumann (2013). Integrated strategic planning of global production networks and financial hedging under uncertain demands and exchange rates. *BuR - Business Research* **6**(2), pp. 215–240.

Kouvelis, P. and J. M. Milner (2002). Supply chain capacity and outsourcing decisions: The dynamic interplay of demand and supply uncertainty. *IIE Transactions* **34**(8), pp. 717–728.

Krankel, R. M., I. Duenyas, and R. Kapuscinski (2006). Timing successive product introductions with demand diffusion and stochastic technology improvement. *Manufacturing & Service Operations Management* **8**(2), pp. 119–135.

Krishnan, V. and S. Gupta (2001). Appropriateness and impact of platform-based product development. *Management Science* **47**(1), pp. 52–68.

Krishnan, V., R. Singh, and D. Tirupati (1999). A model-based approach for planning and developing a family of technology-based products. *Manufacturing & Service Operations Management* **1**(2), pp. 132–156.

Bibliography

Kuhn, H. and T. Schmaußer (2012). Production network planning in the automotive industry. Paper presented at: *2012 International Conference on Advanced Vehicle Technologies and Integration.* Beijing: China Machine Press, pp. 689–695.

Kumar, D., W. Chen, and T. W. Simpson (2009). A market-driven approach to product family design. *International Journal of Production Research* **47**(1), pp. 71–104.

Lampón, J., P. Cabanelas, and J. G. Benito (2015). The impact of implementation of a modular platform strategy in automobile manufacturing networks. *Working paper.*

Lanza, G. and S. Peters (2012). Integrated capacity planning over highly volatile horizons. *CIRP Annals - Manufacturing Technology* **61**(1), pp. 395–398.

Li, H. and S. C. Graves (2012). Pricing decisions during inter-generational product transition. *Production and Operations Management* **21**(1), pp. 14–28.

Li, H., S. C. Graves, and D. B. Rosenfield (2010). Optimal planning quantities for product transition. *Production and Operations Management* **19**(2), pp. 142–155.

Liao, S. and R. W. Seifert (2015). On the optimal frequency of multiple generation product introductions. *European Journal of Operational Research* **245**(3), pp. 805–814.

Lim, L. L., G. Alpan, and B. Penz (2014a). A simulation-optimization approach for managing the sales and operations planning in the automotive industry. *Les cahhiers Leibniz* **212**.

— (2014b). Reconciling sales and operations management with distant suppliers in the automotive industry: A simulation approach. *International Journal of Production Economics* **151**, pp. 20–36.

Liu, H., Q. Zhao, N. Huang, and X. Zhao (2015). Production line capacity planning concerning uncertain demands for a class of manufacturing systems with multiple products. *IEEE/CAA Journal of Automatica Sinica* **2**(2), pp. 217–225.

Liu, H. and O. Özer (2009). Managing a product family under stochastic technological changes. *International Journal of Production Economics* **122**(2), pp. 567–580.

Liu, Z., Y. S. Wong, and K. S. Lee (2011). A manufacturing-oriented approach for multi-platforming product family design with modified genetic algorithm. *Journal of Intelligent Manufacturing* **22**(6), pp. 891–907.

Lobel, I., J. Patel, G. Vulcano, and J. Zhang (2016). Optimizing product launches in the presence of strategic consumers. *Management Science* **62**(6), pp. 1778–1799.

Mariel, K. and S. Minner (2015). Strategic capacity planning in automotive production networks under duties and duty drawbacks. *International Journal of Production Economics* **170-B**, pp. 687–700.

Márkus, A. and J. Váncza (1998). Product line development with customer interaction. *CIRP Annals - Manufacturing Technology* **47**(1), pp. 361–364.

Martinez-Costa, C., M. Mas-Machuca, E. Benedito, and A. Corominas (2014). A review of mathematical programming models for strategic capacity planning in manufacturing. *International Journal of Production Economics* **153**, pp. 66–85.

Matta, A., M. Tomasella, and A. Valente (2007). Impact of ramp-up on the optimal capacity-related reconfiguration policy. *International Journal of Flexible Manufacturing Systems* **19**(3), pp. 173–194.

McKinsey & Company (2016). Automotive revolution - How the convergence of disruptive technology-driven trends could transform the auto industry. Accessed at Feb. 28, 2018. URL: `http://www.mckinsey.com/industries/automotive-and-assembly/our-insights/disruptive-trends-that-will-transform-the-auto-industry`.

Melo, M. T., S. Nickel, and F. Saldanha-da Gama (2009). Facility location and supply chain management - A review. *European Journal of Operational Research* **196**(2), pp. 401–412.

Meyer, M. H., P. Tertzakian, and J. M. Utterback (1997). Metrics for managing research and development in the context of the product family. *Management Science* **43**(1), pp. 88–111.

Meyr, H. (2004). Supply chain planning in the German automotive industry. *OR Spectrum* **26**(4), pp. 447–470.

Mikkola, J. H. (2003). Modularity, component outsourcing, and inter-firm learning. *R&D Management* **33**(4), pp. 439–454.

Moreno, A. and C. Terwiesch (2017). The effects of product line breadth: Evidence from the automotive industry. *Marketing Science* **36**(2), pp. 254–271.

Morgan, L. O., R. L. Daniels, and P. Kouvelis (2001a). Marketing/manufacturing trade-offs in product line management. *IIE Transactions* **33**(11), pp. 949–962.

Morgan, L. O., R. M. Morgan, and W. L. Moore (2001b). Quality and time-to-market trade-offs when there are multiple product generations. *Manufacturing & Service Operations Management* **3**(2), pp. 89–104.

Muffatto, M. (1999). Introducing a platform strategy in product development. *International Journal of Production Economics* **60-61**, pp. 145–153.

Muffatto, M. and M. Roveda (2000). Developing product platforms: Analysis of the development process. *Technovation* **20**(11), pp. 617–630.

Bibliography

Mula, J., D. Peidro, M. Díaz-Madroñero, and E. Vicens (2010). Mathematical programming models for supply chain production and transport planning. *European Journal of Operational Research* **204**(3), pp. 377–390.

Müller, S. and K. Haase (2016). On the product portfolio planning problem with customer-engineering interaction. *Operations Research Letters* **44**(3), pp. 390–393.

Olhager, J., M. Rudberg, and J. Wikner (2001). Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics* **69**(2), pp. 215–225.

Oliva, R. and N. Watson (2011). Cross-functional alignment in supply chain planning: A case study of sales and operations planning. *Journal of Operations Management* **29**(5), pp. 434–448.

Pal Singh Toor, T. and T. Dhir (2011). Benefits of integrated business planning, forecasting, and process management. *Business Strategy Series* **12**(6), pp. 275–288.

Pasche, M. and M. Sköld (2012). Potential drawbacks of component commonality in product platform development. *International Journal of Automotive Technology and Management* **12**(1), pp. 92–108.

Peidro, D., J. Mula, R. Poler, and J.-L. Verdegay (2009). Fuzzy optimization for supply chain planning under supply, demand and process uncertainties. *Fuzzy Sets and Systems* **160**(18), pp. 2640–2657.

Peidro, D., J. Mula, M. Jiménez, and M. del Mar Botella (2010). A fuzzy linear programming based approach for tactical supply chain planning in an uncertainty environment. *European Journal of Operational Research* **205**(1), pp. 65–80.

Peters, S. (2015). Optimal investment policies in premature manufacturing technologies. *International Journal of Production Research* **53**(13), pp. 3963–3974.

Pflug, G. C. and A. Pichler (2016). Time-inconsistent multistage stochastic programs: Martingale bounds. *European Journal of Operational Research* **249**(1), pp. 155–163.

Pil, F. K. and M. Holweg (2004). Linking product variety to order-fulfillment strategies. *Interfaces* **34**(5), pp. 394–403.

Qi, A., H.-S. Ahn, and A. Sinha (2017). Capacity investment with demand learning. *Operations Research* **65**(1), pp. 145–164.

Ramadan, K. and W. ElMaraghy (2014). Product families and platforms diversification: Customer expectations, product variations, or self-competition? *Procedia CIRP* **16**, pp. 104–109.

Ramdas, K. and T. Randall (2008). Does component sharing help or hurt reliability? An empirical study in the automotive industry. *Management Science* **54**(5), pp. 922–938.

Robertson, D. and K. Ulrich (1998). Planning for product platforms. *Sloan Management Review* **39**(4), pp. 19–31.

Rockafellar, R. and S. Uryasev (2000). Optimization of conditional value at risk. *Journal of Risk* **2**(3), pp. 21–41.

Roscher, J. (2008). Bewertung von Flexibilitätsstrategien für die Endmontage in der Automobilindustrie. *Ph.D. thesis.* Stuttgart: Universität Stuttgart.

Sadeghi, A., A. Alem-Tabriz, and M. Zandieh (2011). Product portfolio planning: A metaheuristic-based simulated annealing algorithm. *International Journal of Production Research* **49**(8), pp. 2327–2350.

Salvador, F. (2007). Toward a product system modularity construct: Literature review and reconceptualization. *IEEE Transaction on Engineering Management* **54**(2), pp. 219–240.

Schmaußer, T. (2011). Die strategische Planung globaler Produktionsnetzwerke in der Automobilindustrie. *Ph.D. thesis.* Ingolstadt: Katholische Universität Eichstätt-Ingolstadt.

Schneeweiss, C. (1998). Hierarchical planning in organizations: Elements of a general theory. *International Journal of Production Economics* **56-57**, pp. 547–556.

Schuh, G., J.-C. Desoi, and G. Tücks (2005). Holistic approach for production ramp-up in automotive industry. In: *Advances in Integrated design and manufacturing in mechanical engineering.* Ed. by A. Bramley, D. Brissaud, D. Coutellier, and C. McMahon. Dordrecht: Springer, pp. 255–268.

Seepersad, C. C., G. Hernandez, and J. K. Allen (2000). A quantitative approach to determining product platform extent. Paper presented at: *ASME Design Engineering Technical Conferences.* Sept. 10-13, 2000. Baltimore.

Seepersad, C. C., F. Mistree, and J. K. Allen (2002). A quantitative approach for designing multiple product platforms for an evolving portfolio of products. Paper presented at: *ASME Design Engineering Technical Conferences.* Sept. 29 - Oct. 2, 2002. Montréal.

Sillekens, T. (2008). Aggregierte Produktionsplanung in der Automobilindustrie unter besonderer Berücksichtigung von Personalflexibilität. *Ph.D. thesis.* Paderborn: Universität Paderborn.

Bibliography

Sillekens, T., A. Koberstein, and L. Suhl (2011). Aggregate production planning in the automotive industry with special consideration of workforce flexibility. *International Journal of Production Research* **49**(17), pp. 5055–5078.

Simpson, T. W. (2004). Product platform design and customization: Status and promise. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* **18**(1), pp. 3–20.

Simpson, T. W., J. R. Maier, and F. Mistree (2001). Product platform design: Method and application. *Research in Engineering Design* **13**(1), pp. 2–22.

Simpson, T. W. et al. (2012). From user requirements to commonality specifications: An integrated approach to product family design. *Research in Engineering Design* **23**(2), pp. 141–153.

Stäblein, T. and K. Aoki (2015). Planning and scheduling in the automotive industry: A comparison of industrial practice at German and Japanese makers. *International Journal of Production Economics* **162**, pp. 258–272.

Stephan, H. A., T. Gschwind, and S. Minner (2010). Manufacturing capacity planning and the value of multi-stage stochastic programming under Markovian demand. *Flexible Services and Manufacturing Journal* **22**(3-4), pp. 143–162.

Suh, E. S., O. L. de Weck, I. Y. Kim, and D. Chang (2007). Flexible platform component design under uncertainty. *Journal of Intelligent Manufacturing* **18**(1), pp. 115–126.

Surbier, L., G. Alpan, and E. Blanco (2013). A comparative study on production ramp-up: State-of-the-art and new challenges. *Production Planning & Control* **25**(15), pp. 1264–1286.

Tavares Thomé, A. M., L. F. Scavarda, N. S. Fernandez, and A. J. Scavarda (2012). Sales and operations planning: A research synthesis. *International Journal of Production Economics* **138**(1), pp. 1–13.

Tomino, T., Y. Park, P. Hong, and J. J. Roh (2009). Market flexible customizing system (MFCS) of Japanese vehicle manufacturers: An analysis of Toyota, Nissan and Mitsubishi. *International Journal of Production Economics* **118**(2), pp. 375–386.

Torabi, S. A. and E. Hassini (2009). Multi-site production planning integrating procurement and distribution plans in multi-echelon supply chains: An interactive fuzzy goal programming approach. *International Journal of Production Research* **47**(19), pp. 5475–5499.

Tuomikangas, N. and R. Kaipia (2014). A coordination framework for sales and operations planning (S&OP): Synthesis from the literature. *International Journal of Production Economics* **154**, pp. 243–262.

Ulrich Karl, T. and S. D. Eppinger (2008). Product design and development. 4th ed. New York: McGraw-Hill.

Van Mieghem, J. A. (2003). Capacity management, investment, and hedging: Review and recent developments. *Manufacturing & Service Operations Management* **5**(4), pp. 269–302.

Van den Broeke, M. M. and R. N. Boute (2017). Platform replacement frequency: Managerial decision-making drivers. *Working paper.*

Van den Broeke, M. M., R. N. Boute, and B. Samii (2015). Evaluation of product-platform decisions based on total supply chain costs. *International Journal of Production Research* **53**(18), pp. 5545–5563.

Van den Broeke, M. M., R. N. Boute, B. Cardoen, and B. Samii (2017). An efficient solution method to design the cost-minimizing platform portfolio. *European Journal of Operational Research* **259**(1), pp. 236–250.

Van den Broeke, M. M., R. Boute, and J. A. Van Mieghem (2018). Platform flexibility strategies: R&D investment versus product customer trade-off. *European Journal of Operational Research* **270**(2), pp. 475–486.

Verhoef, P. C., K. H. Pauwels, and M. A. Tuk (2012). Assessing consequences of component sharing across brands in the vertical product line in the automotive market. *Journal of Product Innovation Management* **29**(4), pp. 559–572.

Volling, T. and T. S. Spengler (2011). Modeling and simulation of order-driven planning policies in build-to-order automobile production. *International Journal of Production Economics* **131**(1), pp. 183–193.

Volling, T., A. Matzke, M. Grunewald, and T. S. Spengler (2013). Planning of capacities and orders in build-to-order automobile production: A review. *European Journal of Operational Research* **224**(2), pp. 240–260.

Wang, W., M. E. Ferguson, S. Hu, and G. C. Souza (2013). Dynamic capacity investment with two competing technologies. *Manufacturing & Service Operations Management* **15**(4), pp. 616–629.

Weber, C. A., J. R. Current, and W. C. Benton (1991). Vendor selection criteria and methods. *European Journal of Operational Research* **50**(1), pp. 2–18.

Wittek, K. (2013). Standortübergreifende Programmplanung in flexiblen Produktionsnetzwerken der Automobilindustrie. Wiesbaden: Springer.

Wittek, K., T. Volling, T. S. Spengler, and F.-W. Gundlach (2011). Tactical planning in flexible production networks in the automotive industry. Paper presented at:

Conference on Operations Research. Ed. by B. Hu, K. Morasch, S. Pickl, and M. Siegle. München: Springer, pp. 429–434.

Wittek, K., A. Koberstein, and T. S. Spengler (2012). Mid-term model-plant allocation for flexible production networks in the automotive industry. Paper presented at: *Conference on Operations Research.* Ed. by D. Klatte, H.-J. Lüthi, and K. Schmedders. Zürich: Springer, pp. 433–438.

Wochner, S., M. Grunow, T. Stäblein, and R. Stolletz (2016). Planning for ramp-ups and new product introductions in the automotive industry: Extending sales and operations planning. *International Journal of Production Economics* **182**, pp. 372–383.

Yang, Y. (2009). A screening model to explore planning decisions in automotive manufacturing systems under demand uncertainty. *Ph.D. thesis.* Cambridge: Massachusetts Institute of Technology.

Yelle, L. E. (1979). The learning curve: Historical review and comprehensive survey. *Decision Sciences* **10**(2), pp. 302–328.

Zhang, G., J. Shang, and W. Li (2011). Collaborative production planning of supply chain under price and demand uncertainty. *European Journal of Operational Research* **215**(3), pp. 590–603.

Zhang, L. L. (2015). A literature review on multitype platforming and framework for future research. *International Journal of Production Economics* **168**, pp. 1–12.

Appendix

Appendix A.

Chapter 4

A.1. List of symbols in the capacity planning models

In the following, all symbols of the CPM and CPMR as defined in Section 4.4 are listed and briefly described.

Index sets

$a \in A$ Set of capacity configuration alternatives.

$d \in D$ Set of demand forecasting scenarios.

$f \in F$ Set of fixing periods in the capacity planning project.

$i \in I$ Set of shared manufacturing stages.

$j \in J$ Set of dedicated manufacturing stages.

$r \in R$ Set of probability level intervals for CVaR.

$t \in T$ Set of periods in the capacity planning phase.

$v \in V$ Set of vehicle model derivatives.

Variables

$a_t \in A$ Decision variable: Index of capacity configuration selected in period t.

$\boldsymbol{c}_t = (c_{tf})_{f \in F} \in A^{|F|}$ State variables: Capacity configuration selected for stages fixed in period f as of period t.

$d_t \in D$ Random/state variable: Demand forecasting scenario received prior to period t.

$\boldsymbol{n}_t = (n_{td})_{d \in D} \in (t+1)^{|D|}$ State variables: Number of observations of forecasting scenario d up to period t.

Variables (continued)

$r_t \in R$ State variable: Probability level interval of CVaR in period t.

$\boldsymbol{s}_t = (\boldsymbol{c}_t, d_t, \boldsymbol{n}_t)$ State vector: MDP state of the CPM in period t.

$\boldsymbol{s}_t^R = (\boldsymbol{c}_t, d_t, \boldsymbol{n}_t, r_t)$ State vector: MDP state of the CPMR in period t.

$z_t(d_t) \in \mathbb{R}^+$ Decision/random variable: Densities based on forecasting scenario d_t in period t for dual CVaR representation.

$\gamma_t \in [0,1]$ Random variable: Probability level of CVaR in period t.

Partial state transitions

$\pi_t(d_{t+1}|\boldsymbol{n}_t) \in [0,1]$ Stochastic transition into new demand forecasting scenario d_{t+1}.

$\rho_t(\boldsymbol{c}_{t+1}|\boldsymbol{c}_t, a_t) \in \{0,1\}$ Transition into new capacity configuration $\boldsymbol{c}_{t+1}$.

$\sigma_t(\boldsymbol{n}_{t+1}|\boldsymbol{n}_t, d_{t+1}) \in \{0,1\}$ Transition into new demand forecasting scenario count $\boldsymbol{n}_{t+1}$.

$\varphi_t\big(r_{t+1}|r_t, z_{t+1}(d_{t+1})\big) \in \{0,1\}$ Transition into new probability level interval r_{t+1}.

Parameters

$f_i^I \in F$ Fixing period of shared stage i.

$f_j^J \in F$ Fixing period of dedicated stage j.

$\alpha_d \in \mathbb{N}_0$ Prior information on demand forecasting scenario d.

$\beta \in [0,1]$ Discounting factor.

$\gamma \in [0,1]$ Probability level of CVaR in period $t = 0$.

$\hat{\gamma} \in [0,1]$ Range of probability level intervals for CVaR.

$\theta_{it}^I \in \{0,1\}$ Binary parameter:
1, if shared stage i has fixing period $f_i^I = t + 1$; 0, otherwise.

$\theta_{jt}^J \in \{0,1\}$ Binary parameter:
1, if shared stage j has fixing period $f_j^J = t + 1$; 0, otherwise.

$\lambda_i^I(a) \in \mathbb{R}^+$ Investment costs of shared stage i in configuration a.

$\lambda_j^J(a) \in \mathbb{R}^+$ Investment costs of dedicated stage j in configuration a.

Functions

$NPV^{LCM}(\boldsymbol{s}_{|T|}) \in \mathbb{R}$ Optimized NPV resulting from LCM.

$v_t^R(\boldsymbol{s}_t^R, a_t) \in \mathbb{R}$ objective function of inner minimization in the CPMR.

$V_t(\boldsymbol{s}_t) \in \mathbb{R}$ Value function of MDP for CPM in period t.

$V_t^R(\boldsymbol{s}_t^R) \in \mathbb{R}$ Value function of MDP for CPMR in period t.

A.2. Lifecycle model

In the following, the LCM is presented. The LCM is based on a MILP. It optimizes the lifecycle performance for the considered derivatives based on the termination state $\mathbf{s}_T$ of the CPM and the CPMR. Additional parameters and decision variables are introduced in the following. We focus merely on the core decisions during the lifecycle, i.e. production volumes as well as the selection of operating modes and workforce levels.

Decision variables

$x_{lv} \in \mathbb{R}^+$	Production volume of derivative v in lifecycle period l.
$y_{lis}^I \in \{0,1\}$	1, if mode s is selected for shared stage i in lifecycle period l; 0, otherwise.
$y_{ljs}^J \in \{0,1\}$	1, if mode s is selected for dedicated stage j in lifecycle period l; 0, otherwise.
$z_{lis}^I \in \mathbb{R}^+$	Workers in shared stage i in lifecycle period l deployed in mode s.
$z_{ljs}^J \in \mathbb{R}^+$	Workers in dedicated stage j in lifecycle period l deployed in mode s.
$z_{li}^{HI} \in \mathbb{R}^+$	Workers hired for shared stage i in lifecycle period l.
$z_{lj}^{HJ} \in \mathbb{R}^+$	Workers hired for dedicated stage j in lifecycle period l.
$z_{li}^{DI} \in \mathbb{R}^+$	Workers dismissed in shared stage i in lifecycle period l.
$z_{lj}^{DJ} \in \mathbb{R}^+$	Workers dismissed in dedicated stage j in lifecycle period l.

Additional parameters

$\delta_{dlv} \in \mathbb{R}^+$	Demand volume of demand scenario d in lifecycle period l for derivative v.
$\eta_{dlv} \in \mathbb{R}^+$	Price per unit of demand scenario d in lifecycle period l for derivative v.
$\iota \in \mathbb{R}^+$	Lost sales factor (share of unfulfilled demand moving to competition).
$\zeta_{ias}^I \in \mathbb{R}^+$	Annual capacity level for shared stage i in capacity level a and operating mode s.
$\zeta_{jas}^J \in \mathbb{R}^+$	Annual capacity level for dedicated stage j in level a and operating mode s.
$\epsilon_{iv}^I \in \mathbb{R}^+$	Capacity consumption on shared stage i for derivative v.
$\psi_{iav}^I \in \mathbb{R}^+$	Variable vehicle cost in capacity level a on shared stage i for derivative v.
$\psi_{ja}^J \in \mathbb{R}^+$	Variable vehicle cost in capacity level a on dedicated stage j.

Additional parameters (continued)

$\tau_{ias}^{I} \in \mathbb{R}^{+}$ Workers needed to operate capacity level a on shared stage i in operating mode s.

$\tau_{jas}^{J} \in \mathbb{R}^{+}$ Workers needed to operate level a on dedicated stage j in operating mode s.

$\upsilon_{i}^{I} \in \mathbb{R}^{+}$ Annual salary of a worker in shared stage i.

$\upsilon_{j}^{J} \in \mathbb{R}^{+}$ Annual salary of a worker in dedicated stage j.

$\nu_{i}^{I} \in \mathbb{R}^{+}$ Hiring cost of one worker in shared stage i.

$\nu_{j}^{J} \in \mathbb{R}^{+}$ Hiring cost of one worker in dedicated stage j.

$o_{i}^{I} \in \mathbb{R}^{+}$ Dismissal cost of one worker in shared stage i.

$o_{j}^{J} \in \mathbb{R}^{+}$ Dismissal cost of one worker in dedicated stage j.

$\chi_{s} \in [0,1]$ Salary increase for mode s (overtime, weekend shift, etc.).

$\Omega^{I} \in \mathbb{R}^{+}$ Additional capacity consumption during periods with ramp-ups in Shared stage i.

$\Omega_{j}^{J} \in \mathbb{R}^{+}$ Additional capacity consumption during periods with ramp-ups in Body shop j.

$\Delta_{vl} \in \{0,1\}$ 1, if derivative v has its SOP in lifecycle period l; 0, otherwise.

The LCM is defined with objective function (A.1) maximizing the NPV of the lifecycle, capacity constraints (A.2) and (A.3) for shared stages and dedicated stages accounting for ramp-up efficiency losses, constraints (A.4) and (A.5) enforcing the operating mode selection for every lifecycle period, constraints (A.6) to (A.7) and (A.8) to (A.9) for tracking the level and balance of the workforce, constraint (A.10) setting the demand volume as upper bound for the production, and other domains (A.11) to (A.14). The demand volume for the lifecycle phase is initialized according to the forecast scenario $d_{|T|}$. Configuration-depending parameters are initialized based on $\mathbf{c}_{|T|} = (c_{|T|f})_{f \in F}$ and θ_{if}^{I} (θ_{jf}^{J}).

$$
\max NPV = \sum_{l \in L} \beta^{l} \left[\sum_{v \in V} \left[\eta_{d_{|T|},lv} - \sum_{i \in I} \sum_{f \in} \psi_{ic_{|T|f}v}^{I} \theta_{if}^{I} - \sum_{f \in F} \psi_{vc_{|T|f}}^{J} \theta_{v,f-1}^{J} \right] x_{lv} \right.
$$
$$
- \sum_{i \in I} \sum_{s \in S} \left[z_{lis}^{I} \chi_{s} \upsilon_{i}^{I} + \nu_{i}^{I} z_{li}^{HI} + o_{i}^{I} z_{li}^{DI} \right]
$$
$$
\left. - \sum_{j \in J} \sum_{s \in S} \left[z_{ljs}^{J} \chi_{s} \upsilon_{j}^{J} + \nu_{j}^{J} z_{lj}^{HJ} + o_{j}^{J} z_{lj}^{DJ} \right] \right] \tag{A.1}
$$

subject to

$$\sum_{v \in V} \epsilon_{iv}^I \left[\prod_{v' \in V} (1 - \Delta_{v'l}) + \left[1 - \prod_{v' \in V} (1 - \Delta_{v'l}) \right] (1 + \Omega_i^I) \right] x_{lv}$$

$$\leq \sum_{s \in S} \left[\sum_{f \in F} \zeta_{ic_{|T|fs}}^I \theta_{if}^I \right] y_{lis}^I \quad \forall i \in I, \forall l \in L \qquad (A.2)$$

$$[(1 - \Delta_{vl}) + \Delta_{vl}(1 + \Omega_j^J)] x_{lv} \leq \sum_{s \in S} \left[\sum_{f \in F} \zeta_{jc_{|T|fs}}^J \theta_{jf}^J \right] y_{ljs}^J \quad \forall l \in L, \forall v \in V \qquad (A.3)$$

$$\sum_{s \in S} y_{lis}^I = 1 \quad \forall i \in I, \forall l \in L \qquad (A.4)$$

$$\sum_{s \in S} y_{ljs}^J = 1 \quad \forall j \in J, \forall l \in L \qquad (A.5)$$

$$z_{lis}^I \geq \left[\sum_{f \in F} \tau_{ic_{|T|fs}}^I \theta_{if}^I \right] y_{lis}^I \quad \forall i \in I, \forall l \in L, \forall s \in S \qquad (A.6)$$

$$z_{ljs}^J \geq \left[\sum_{f \in F} \tau_{jc_{|T|fs}}^J \theta_{jf}^J \right] y_{ljs}^J \quad \forall j \in J, \forall l \in L, \forall s \in S \qquad (A.7)$$

$$\sum_{s \in S} z_{lis}^I = z_{li}^{HI} - z_{li}^{DI} + \sum_{s \in S} z_{l-1,is}^I \quad \forall i \in I, \forall l \in L \qquad (A.8)$$

$$\sum_{s \in S} z_{ljs}^J = z_{lj}^{HJ} - z_{lj}^{DJ} + \sum_{s \in S} z_{l-1,js}^J \quad \forall j \in J, \forall l \in L \qquad (A.9)$$

$$x_{lv} \leq \delta_{d_{|T|}lv}, x_{lv} \geq 0 \quad \forall l \in L, \forall v \in V \qquad (A.10)$$

$$z_{lis}^I \geq 0, y_{lis}^I \in \{0, 1\} \quad \forall i \in I, \forall l \in L, \forall s \in S \qquad (A.11)$$

$$z_{ljs}^J \geq 0, y_{ljs}^J \in \{0, 1\} \quad \forall j \in J, \forall l \in L, \forall s \in S \qquad (A.12)$$

$$z_{li}^{HI}, z_{li}^{DI} \geq 0 \quad \forall i \in I, \forall l \in L \qquad (A.13)$$

$$z_{lj}^{HJ}, z_{lj}^{DJ} \geq 0 \quad \forall j \in J, \forall l \in L \qquad (A.14)$$

A.3. Bayesian updating for forecasting scenarios

In the following, we present the details on the derivation of the Bayesian estimate $\bar{\boldsymbol{\pi}}_t = (\bar{\pi}_{td})_{d \in D}$ for the probabilities of the forecasting scenarios. The observation of forecast $d \in D$ in a period is assumed to be a Bernoulli event with probability π_d. Thus, $\boldsymbol{n}_t = (n_{td})_{d \in D}$ follows the multinomial distribution with known parameter $N_t = \sum_{d \in D} n_{td} = t + 1$ and unknown parameters $\boldsymbol{\pi} = (\pi_d)_{d \in D}$, i.e. $\boldsymbol{n}_t \sim M(N_t, \boldsymbol{\pi})$ (Chen et al., 2010). The resulting

probability to observe a specific forecasting history $\boldsymbol{n}_t$ is defined as

$$\Phi(\boldsymbol{n}_t|\bar{\boldsymbol{\pi}}) = \binom{N_t}{n_{t0}...n_{t|D|}} \prod_{d \in D} \pi_d^{n_{td}}.$$

Furthermore, the prior distribution of unknown parameters $\boldsymbol{\pi} = (\pi_d)_{d \in D}$ follows the Dirichlet distribution with parameters $\boldsymbol{\alpha} = (\alpha_d)_{d \in D}$, $\alpha_d > 0$, i.e. $\boldsymbol{\pi} \sim Dir(\boldsymbol{\alpha})$. $\boldsymbol{\alpha}$ synthesizes prior knowledge of the capacity planners, e.g. expert knowledge or information collected before period $t = 0$. Thus, the resulting density function of $\boldsymbol{\pi}$ is defined as

$$\phi(\boldsymbol{\pi}) = \frac{\Gamma(\sum_{d \in D} \alpha_d)}{\prod_{d \in D} \Gamma(\alpha_d)} \prod_{d \in D} \pi_d^{\alpha_d - 1},$$

with $\Gamma(...)$ denoting the value of the Gamma function. The posterior distribution of $\boldsymbol{\pi}$ in period t is also Dirichlet distributed with parameters $\boldsymbol{\alpha} + \boldsymbol{n}_t$, i.e. $\boldsymbol{\pi}_t \sim Dir(\boldsymbol{\alpha} + \boldsymbol{n}_t)$. The resulting density function is

$$\phi(\boldsymbol{\pi}_t|\boldsymbol{n}_t) = \frac{\Gamma(\sum_{d \in D} \alpha_d + n_{td})}{\prod_{d \in D} \Gamma(\alpha_d + n_{td})} \prod_{d \in D} \pi_d^{\alpha_d + n_{td} - 1}.$$

Thus, the Bayesian estimate for probabilities $\bar{\boldsymbol{\pi}}_t = (\bar{\pi}_{td})_{d \in D}$ in period t is defined as

$$\bar{\pi}_{td} = E(\pi_{td}|\boldsymbol{n}_t) = \frac{\alpha_d + n_{td}}{\sum_{d' \in D} \alpha_{d'} + n_{td'}},$$

which is updated every period of the capacity project phase.

A.4. Decomposition theorem for the conditional value at risk

We present the decomposition theorem defined by Pflug and Pichler (2016). Based on the dual representation of the CVaR, it is defined for random variable V and constant probability level $\gamma \in [0, 1]$ as

$$CVaR_\gamma(V) = \inf_z \{E[Vz] : z \geq 0, z \leq \frac{1}{\gamma} \wedge E[z] = 1\}. \tag{A.15}$$

Note that random variables z are densities with the optimal z being anti-monotone to V.

In the dynamic setup, $CVaR_\gamma(V)$ quantifies the future risk in period $t = 0$ and is defined on $L^\infty(\mathcal{F}_{|T|})$, where $\mathcal{F}_{|T|}$ is the sigma algebra measuring the information at time horizon T. Consequently, at an intermediate period $t > 0$, sigma algebra $\mathcal{F}_t$ with $\mathcal{F}_t \subset \mathcal{F}_{|T|}$ reflects the information available up to period t. The probability level γ becomes an $\mathcal{F}_t$ measurable random variable defined as $\gamma_t \in [0, 1]$.

Based on these definitions, the decomposition of the CVaR of random variable $V \in L^\infty(\mathcal{F}_{|T|})$ and sigma algebra $\mathcal{F}_t \subset \mathcal{F}_{|T|}$ is defined as follows (for more details we refer to Pflug and Pichler, 2016):

1. The CVaR at deterministic probability level $\gamma \in [0, 1]$ in period 0 is defined as

$$CVaR_\gamma(V) = \inf_{z_t} E[z_t CVaR_{\gamma z_t}(V|\mathcal{F}_t)], \tag{A.16}$$

   where z_t are all $\mathcal{F}_t$-measurable densities with $z_t \geq 0$, $z_t \leq \frac{1}{\gamma}$ and $E[z_t] = 1$ and the infimum being attained for $\gamma > 0$.

2. For z as the optimal dual density of (A.15), the best choice in (A.16) is $z_t = E(z|\mathcal{F}_t)$.

3. For nested sigma algebras $\mathcal{F}_t \subset \mathcal{F}_\tau \subset \mathcal{F}_{|T|}$, the CVaR at random and $\mathcal{F}_t$-measurable probability level $\gamma_t \in [0, 1]$ has the recursive formulation

$$CVaR_{\gamma_t}(V|\mathcal{F}_t) = \text{ess} \inf_{z_\tau} E[z_\tau CVaR_{\gamma_t z_\tau}(V|\mathcal{F}_t)|\mathcal{F}_t],$$

   where z_τ are all $\mathcal{F}_\tau$-measurable densities with $z_\tau \geq 0$, $z_\tau \leq \frac{1}{\gamma_t}$ and $E[z_\tau|\mathcal{F}_t] = 1$.

A.5. Benchmark model

In the following, the 2SP and the 2SPR are presented, which are used as benchmark models in Chapter 4.5.2. The 2SP(R) is based on two-stage stochastic programming with recourse, applied in a rolling horizon scheme during the capacity project phase. To implement the time-phased decision making, each of the sets I and J is split into three sets and updated before the decision making in the current period $t^* \in T$ of the rolling horizon scheme according to the decision history as well as to f_i^I and f_j^J. Based on the sets I_x and J_x, $x \in \{1, 2, 3\}$, updated for the current period t^*, the parameters are initialized and the decision variables defined. Most parameters are the same as in the CPM(R)-LCM. New parameters and decision variables are defined in the following.

Additional index sets

$I_x(J_x)$ $x = 1$: Shared (dedicated) stages already fixed, $f_i^I(f_j^J) < t^* + 1$.

   $x = 2$: Shared (dedicated) stages with fixing period, $f_i^I(f_j^J) = t^* + 1$.

   $x = 3$: Shared (dedicated) stages with later fixing period, $f_i^I(f_j^J) > t^* + 1$.

Decision variables

$a_a^1 \in \{0, 1\}$ Capacity level for stages i (j) with fixing period $f_i^I(f_j^J) = t^* + 1$;
   1, if capacity level a is chosen; 0, otherwise.

$a_{ad}^2 \in \{0, 1\}$ Capacity level for stages i (j) with fixing period $f_i^I(f_j^J) > t^* + 1$;
   1, if capacity level a is chosen in scenario d; 0, otherwise.

$x_{dl(a)v}^{I_x} \in \mathbb{R}^+$ Production volume of vehicle v in lifecycle period l and scenario d;
   $x = 1$: On shared stages with fixing period $f_i^I < t^* + 1$.
   $x = 2$: Config. a on shared stages with fixing period $f_i^I = t^* + 1$.
   $x = 3$: Config. a on shared stages with fixing period $f_i^I > t^* + 1$.

$x_{dl(a)j}^{J_x} \in \mathbb{R}^+$ Production volume in lifecycle period l and scenario d;
   $x = 1$: On dedicated stage $j \in J_1(f_j^J < t^* + 1)$.
   $x = 2$: In configuration a on dedicated stage $j \in J_2(f_j^J = t^* + 1)$.
   $x = 3$: In configuration a on dedicated stage $j \in J_3(f_j^J > t^* + 1)$.

$z_{dlis}^{I_x} \in \mathbb{R}^+$ Workers employed in mode s, lifecycle period l and scenario d;
   $x = 1$: On shared stage $i \in I_1(f_i^I < t^* + 1)$.
   $x = 2$: On shared stage $i \in I_2(f_i^I = t^* + 1)$.
   $x = 3$: On shared stage $i \in I_3(f_i^I > t^* + 1)$.

$z_{dljs}^{J_x} \in \mathbb{R}^+$ Equivalent to $z_{dlis}^{I_x}$.

$z_{dli}^{HI_x} \in \mathbb{R}^+$ Workers hired in lifecycle period l and scenario d;
   $x = 1$: For shared stage $i \in I_1(f_i^I < t^* + 1)$.
   $x = 2$: For shared stage $i \in I_2(f_i^I = t^* + 1)$.
   $x = 3$: For shared stage $i \in I_3(f_i^I > t^* + 1)$.

$z_{dli}^{DI_x} \in \mathbb{R}^+$ Workers fired in lifecycle period l and scenario d;
   $x = 1$: For shared stage $i \in I_1(f_i^I < t^* + 1)$.
   $x = 2$: For shared stage $i \in I_2(f_i^I = t^* + 1)$.
   $x = 3$: For shared stage $i \in I_3(f_i^I > t^* + 1)$.

$z_{dlj}^{HJ_x} \in \mathbb{R}^+$ Equivalent to $z_{dli}^{HI_x}$.

$z_{dlj}^{DJ_x} \in \mathbb{R}^+$ Equivalent to $z_{dli}^{DI_x}$.

Additional decision variables (continued)

$y^{I_x}_{dl(a)is} \in \{0, 1\}$ 1, if mode s is selected in lifecycle period l and scenario d;

0, otherwise;

$x = 1$: For shared stage $i \in I_1(f^I_i < t^* + 1)$.

$x = 2$: In configuration a for shared stage $i \in I_2(f^I_i = t^* + 1)$.

$x = 3$: In configuration a for shared stage $i \in I_3(f^I_i > t^* + 1)$.

$y^{J_x}_{dl(a)js} \in \{0, 1\}$ Equivalent to $y^{I_x}_{dl(a)is}$.

$NPV_{d \in \mathbb{R}}$ NPV of scenario d (2SPR only).

$u_d \in \mathbb{R}^+$ Auxiliary variable for demand scenario d (2SPR only).

$VaR \in \mathbb{R}$ VaR (2SPR only).

Additional parameters

$\Psi^{J_x}_{jv} \in \{0, 1\}$ $x = 1$: 1, if v is produced on dedicated stage $j \in J_1(f^J_j < t^* + 1)$;

0, otherwise.

$x = 2$: 1, if v is produced on dedicated stage $j \in J_2(f^J_j = t^* + 1)$;

0, otherwise.

$x = 3$: 1, if v is produced on dedicated stage $j \in J_3(f^J_j > t^* + 1)$;

0, otherwise.

The 2SP maximizes the expected NPV in t^* based on the Bayesian probability estimates $\bar{\pi}_{t^*d}$. It is defined by objective function (A.17), constraints (A.18) and (A.19) enforcing the selection of exactly one capacity configuration on the first stage as well as for every forecasting scenario on the second stage, and constraints (A.20) to (A.51) as constraints equivalent to the LCM in Appendix A.2.

$$\max E(NPV_{t^*}) = \sum_{a \in A} a_a^1 \left[\sum_{i \in I_2} \left(-\lambda_i^{I_2}(a) \right) + \sum_{j \in J_2} \left(-\lambda_j^{J_2}(a) \right) \right]$$

$$+ \sum_{d \in D} \bar{\pi}_{t^* d} \left[\sum_{a \in A} a_{ad}^2 \left[\sum_{i \in I_3} \left(-\lambda_i^{I_3}(a) \right) \beta^{\sum_{f=t^*+1}^{F} f\theta_{if}^{I_3} - t^*} + \sum_{j \in J_3} \left(-\lambda_j^{J_3}(a) \right) \beta^{\sum_{f=t^*+1}^{F} f\theta_{jf}^{J_3} - t^*} \right] \right.$$

$$\sum_{l \in L} \beta^{l + |T| - t^*} \left[\sum_{j \in J_1} \left[\sum_{v \in V} \eta_{dlv} \Psi_{jv}^{J_1} - \psi_j^{J_1} \right] x_{dlj}^{J_1} \right.$$

$$+ \sum_{a \in A} \sum_{j \in J_{x:x \in \{2,3\}}} \left[\sum_{v \in V} \eta_{dlv} \Psi_{jv}^{J_x} - \psi_{aj}^{J_x} \right] x_{dlaj}^{J_x}$$

$$- \sum_{v \in V} \sum_{i \in I_1} \psi_{iv}^{I_1} x_{dlv}^{I_1} - \sum_{a \in A} \sum_{v \in V} \sum_{i \in I_{x:x \in \{2,3\}}} \psi_{iav}^{I_x} x_{dlav}^{I_x}$$

$$- \sum_{i \in I_{x:x \in \{1,2,3\}}} \left[\sum_{s \in S} \upsilon_i^{I_x} \chi_s z_{dlis}^{I_x} + \nu_i^{I_x} z_{dli}^{HI_x} + o_i^{I_x} z_{dli}^{DI_x} \right]$$

$$\left. \left. - \sum_{j \in J_{x:x \in \{1,2,3\}}} \left[\sum_{s \in S} \upsilon_j^{J_x} \chi_s z_{dljs}^{J_x} + \nu_j^{J_x} z_{dlj}^{HJ_x} + {}_j^{J_x} z_{dlj}^{DJ_x} \right] \right] \right]$$

$$\text{(A.17)}$$

subject to

$$\sum_{a \in A} a_a^1 = 1 \tag{A.18}$$

$$\sum_{a \in A} a_{ad}^2 = 1 \quad \forall d \in D \tag{A.19}$$

$$\sum_{v \in V} \epsilon_{iv}^{I_1} x_{dlv}^{I_1} \left[\prod_{v' \in V} (1 - \Delta_{v'l}) + \left[1 - \prod_{v' \in V} (1 - \Delta_{v'l}) \right] (1 + \Omega_i^{I_1}) \right] \le \sum_{s \in S} \zeta_{is}^{I_1} y_{dlis}^{I_1}$$

$$\forall d \in D, \forall i \in I_1, \forall l \in L \tag{A.20}$$

$$\sum_{v \in V} \epsilon_{iv}^{I_x} x_{dlav}^{I_x} \left[\prod_{v' \in V} (1 - \Delta_{v'l}) + \left[1 - \prod_{v' \in V} (1 - \Delta_{v'l}) \right] (1 + \Omega_i^{I_x}) \right] \le \sum_{s \in S} \zeta_{ias}^{I_x} y_{dlais}^{I_x}$$

$$\forall a \in A, \forall d \in D, \forall i \in I_{x:x \in \{2,3\}}, \forall l \in L \tag{A.21}$$

$$\left[\sum_{v\in V}\Psi_{jv}^{J_1}\big[(1-\Delta_{vl})+\Delta_{vl}(1+\Omega_j^{J_1})\big]\right]x_{dlj}^{J_1}\le\sum_{s\in S}\zeta_{js}^{J_1}y_{dljs}^{J_1}$$

$$\forall d\in D,\forall j\in J_1,\forall l\in L \qquad\qquad (A.22)$$

$$\left[\sum_{v\in V}\Psi_{jv}^{J_x}\big[(1-\Delta_{vl})+\Delta_{vl}(1+\Omega_j^{J_x})\big]\right]x_{dlaj}^{J_x}\le\sum_{s\in S}\zeta_{jas}^{J_x}y_{dljas}^{J_x}$$

$$\forall a\in A,\forall d\in D,\forall j\in J_{x:x\in\{2,3\}},\forall l\in L \qquad\qquad (A.23)$$

$$x_{dlj}^{J_1}\le\sum_{v}\Psi_{jv}^{J_1}\delta_{dlv}\quad\forall d\in D,\forall j\in J_1,\forall l\in L \qquad\qquad\qquad (A.24)$$

$$x_{dlaj}^{J_x}\le\sum_{v\in V}\Psi_{jv}^{J_x}\delta_{dlv}\quad\forall a\in A,\forall d\in D,\forall j\in J_{x:x\in\{2,3\}},\forall l\in L \qquad (A.25)$$

$$x_{dlv}^{I_1}\ge\sum_{j\in J_1}x_{dlj}^{J_1}\Psi_{jv}^{J_1}+\sum_{a\in A}\sum_{j\in J_{x:x\in\{2,3\}}}x_{dlaj}^{J_x}\Psi_{jv}^{J_x}$$

$$\forall d\in D,\forall l\in L,\forall v\in V \qquad\qquad (A.26)$$

$$\sum_{a\in A}x_{dlav}^{I_x}\ge\sum_{j\in J_1}x_{dlj}^{J_1}\Psi_{jv}^{J_1}+\sum_{a\in A}\sum_{j\in J_{y:y\in\{2,3\}}}x_{dlaj}^{J_y}\Psi_{jv}^{J_y}$$

$$\forall d\in D,\forall l\in L,\forall v\in V,\forall x\in\{2,3\} \qquad\qquad (A.27)$$

$$\sum_{s\in S}y_{dlis}^{I_1}=1\quad\forall d\in D,\forall i\in I_1,\forall l\in L \qquad\qquad\qquad (A.28)$$

$$\sum_{s\in S}y_{dlais}^{I_x}=1\quad\forall a\in A,\forall d\in D,\forall i\in I_{x:x\in\{2,3\}},\forall l\in L \qquad (A.29)$$

$$\sum_{s\in S}y_{dljs}^{J_1}=1\quad\forall d\in D,\forall j\in J_1,\forall l\in L \qquad\qquad\qquad (A.30)$$

$$\sum_{s\in S}y_{dlajs}^{J_x}=1\quad\forall a\in A,\forall d\in D,\forall j\in J_{x:x\in\{2,3\}},\forall l\in L \qquad (A.31)$$

$$z_{dlis}^{I_1} \geq \tau_{is}^{I_1} y_{dlis}^{I_1} \quad \forall d \in D, \forall i \in I_1, \forall l \in L, \forall s \in S \tag{A.32}$$

$$z_{dlis}^{I_x} \geq \tau_{ias}^{I_x} y_{dlais}^{I_x} \quad \forall a \in A, \forall d \in D, \forall i \in I_{x:x \in \{2,3\}}, \forall l \in L, \forall s \in S \tag{A.33}$$

$$z_{dljs}^{J_1} \geq \tau_{js}^{J_1} y_{dljs}^{J_1} \quad \forall d \in D, \forall j \in J_1, \forall l \in L, \forall s \in S \tag{A.34}$$

$$z_{dljs}^{J_x} \geq \tau_{jas}^{J_x} y_{dlajs}^{J_x} \quad \forall a \in A, \forall d \in D, \forall j \in J_{x:x \in \{2,3\}}, \forall l \in L, \forall s \in S \tag{A.35}$$

$$\sum_{s \in S} z_{dlis}^{I_x} = z_{dli}^{HI_x} - z_{dli}^{DI_x} + \sum_{s \in S} z_{d,l-1,is}^{I_x} \quad \forall d \in D, \forall i \in I_{x:x \in \{1,2,3\}}, \forall l \in L \tag{A.36}$$

$$\sum_{s \in S} z_{dljs}^{J_x} = z_{dlj}^{HJ_x} - z_{dlj}^{DJ_x} + \sum_{s \in S} z_{d,l-1,js}^{J_x} \quad \forall d \in D, \forall j \in J_{x:x \in \{1,2,3\}}, \forall l \in L \tag{A.37}$$

$$a_a^1 \in \{0,1\} \quad \forall a \in A \tag{A.38}$$

$$a_{ad}^2 \in \{0,1\} \quad \forall a \in A, \forall d \in D \tag{A.39}$$

$$x_{dlv}^{I_1} \geq 0 \quad \forall d \in D, \forall l \in L, \forall v \in V \tag{A.40}$$

$$x_{dlav}^{I_x} \geq 0 \quad \forall a \in A, \forall d \in D, \forall l \in L, \forall v \in V, \forall x \in \{2,3\} \tag{A.41}$$

$$x_{dlj}^{J_1} \geq 0 \quad \forall d \in D, \forall j \in J_1, \forall l \in L \tag{A.42}$$

$$x_{dlaj}^{J_x} \geq 0 \quad \forall a \in A, \forall d \in D, \forall j \in J_{x:x \in \{2,3\}}, \forall l \in L \tag{A.43}$$

$$z_{dlis}^{I_x} \geq 0 \quad \forall d \in D, \forall i \in I_{x:x \in \{1,2,3\}}, \forall l \in L, \forall s \in S \tag{A.44}$$

$$z_{dljs}^{J_x} \geq 0 \quad \forall d \in D, \forall j \in J_{x:x \in \{1,2,3\}}, \forall l \in L, \forall s \in S \tag{A.45}$$

$$y_{dlis}^{I_1} \in \{0,1\} \quad \forall d \in D, \forall i \in I_1, \forall l \in L, \forall s \in S \tag{A.46}$$

$$y_{dlais}^{I_x} \in \{0,1\} \quad \forall a \in A, \forall d \in D, \forall i \in I_{x:x \in \{2,3\}}, \forall l \in L, \forall s \in S \tag{A.47}$$

$$y_{dljs}^{J_1} \in \{0,1\} \quad \forall d \in D, \forall j \in J_1, \forall l \in L, \forall s \in S \tag{A.48}$$

$$y_{dlajs}^{J_x} \in \{0,1\} \quad \forall a \in A, \forall d \in D, \forall j \in J_{x:x \in \{2,3\}}, \forall l \in L, \forall s \in S \tag{A.49}$$

$$z_{dli}^{HI_x} \geq 0, z_{dli}^{DI_x} \geq 0 \quad \forall d \in D, \forall i \in I_{x:x \in \{1,2,3\}}, \forall l \in L \tag{A.50}$$

$$z_{dlj}^{HJ_x} \geq 0, z_{dlj}^{DJ_x} \geq 0 \quad \forall d \in D, \forall j \in J_{x:x \in \{1,2,3\}}, \forall l \in L \tag{A.51}$$

The 2SPR maximizes the CVaR with probability level γ in t^* based on the probability estimates $\bar{\pi}_{t^*d}$. It is defined in accordance with Rockafellar and Uryasev (2000) by the objective function (A.52), the new constraints (A.53) to (A.57) necessary for the CVaR calculation, as well as the constraints (A.38) to (A.51) defined for the 2SP.

$$\max CVaR = VaR - \frac{1}{\gamma} \sum_{d \in D} \bar{\pi}_{t'd} u_d \tag{A.52}$$

subject to

$$
\begin{aligned}
NPV_d = &\sum_{a \in A} a_a^1 \Big[\sum_{i \in I_2} \big(-\lambda_i^{I_2}(a) \big) + \sum_{j \in J_2} \big(-\lambda_j^{J_2}(a) \big) \Big] \\
&+ \sum_{a \in A} a_{ad}^2 \Big[\sum_{i \in I_3} \big(-\lambda_i^{I_3}(a) \big) \beta^{\sum_{f=t^*+1}^{F} f \theta_{if}^{I_3} - t^*} + \sum_{j \in J_3} \big(-\lambda_j^{J_3}(a) \big) \beta^{\sum_{f=t^*+1)}^{F} f \theta_{jf}^{J_3} - t^*} \Big] \\
&+ \sum_{l \in L} \beta^{l+|T|-t^*} \Big[\sum_{j \in J_1} \Big[\sum_{v \in V} \eta_{dlv} \Psi_{jv}^{J_1} - \psi_j^{J_1} \Big] x_{dlj}^{J_1} \\
&\qquad + \sum_{a \in A} \sum_{j \in J_{x:x \in \{2,3\}}} \Big[\sum_{v \in V} \eta_{dlv} \Psi_{jv}^{J_x} - \psi_{aj}^{J_x} \Big] x_{dlaj}^{J_x} \\
&\qquad - \sum_{v \in V} \sum_{i \in I_1} \psi_{iv}^{I_1} x_{dlv}^{I_1} - \sum_{a \in A} \sum_{v \in V} \sum_{i \in I_{x:x \in \{2,3\}}} \psi_{i(a)v}^{I_x} x_{dl(a)v}^{I_x} \\
&\qquad - \sum_{i \in I_{x:x \in \{1,2,3\}}} \Big[\sum_{s \in S} \upsilon_i^{I_x} \chi_s z_{dlis}^{I_x} + \nu_i^{I_x} z_{dli}^{HI_x} + o_i^{I_x} z_{dli}^{DI_x} \Big] \\
&\qquad - \sum_{j \in J_{x:x \in \{1,2,3\}}} \Big[\sum_{s \in S} \upsilon_j^{J_x} \chi_s z_{dljs}^{J_x} + \nu_j^{J_x} z_{dlj}^{HJ_x} + o_j^{J_x} z_{dlj}^{DJ_x} \Big] \Big] \\
& \hspace{10cm} \forall d \in D \tag{A.53}
\end{aligned}
$$

$$u_d \geq VaR - NPV_d \quad \forall d \in D \tag{A.54}$$

$$u_d \geq 0 \quad \forall d \in D \tag{A.55}$$

$$NPV_d \in \mathbb{R} \quad \forall d \in D \tag{A.56}$$

$$VaR \in \mathbb{R} \tag{A.57}$$

Equations $(A.38)$ to $(A.51)$

A.6. Proof of Proposition 4.1

We define the following:

- $\boldsymbol{d}_t = (d_1, ..., d_t), d_t \in D^t$ as the forecasting realizations up to period t.

- $\hat{\boldsymbol{a}}_t^{(B)}$ as the decision history up to period t of the capacity project determined by the CPM-LCM and the 2SP (B), respectively, based on forecasting realizations d_t:

$$\hat{\boldsymbol{a}}_t^{(B)}(\boldsymbol{d}_t) = \big(\hat{a}_0^{(B)}, \hat{a}_1^{(B)}(d_1), ..., \hat{a}_t^{(B)}(d_t)\big), d_\tau \in D \ \forall \tau = 1, ..., t.$$

- $\boldsymbol{A}_t^{(B),*}$ as the configuration tree from period t to $|T| - 1$ determined by the CPM-LCM or the 2SP (B), based on forecasting realizations $\boldsymbol{d}_t$ and decision history $\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1})$:

$$\boldsymbol{A}_t^{(B),*}\big(\boldsymbol{d}_t, \hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1})\big) =$$
$$\Big\{ a_t^{(B),*} \in A, \Big\{ a_\tau^{(B),*}(d_{t+1}, ..., d_\tau) \in A \Big| (d_{t+1}, ..., d_\tau) \in D^{\tau-t} \wedge \tau \in \{t+1, ..., |T| - 1\} \Big\}$$
$$\Big| \boldsymbol{d}_t, \hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}(t-1)) \Big\}.$$

- $v_t(a_t) = -\sum_{i \in I} \lambda_i^I(a_t)\theta_{it}^I - \sum_{j \in J} \lambda_j^J(a_t)\theta_{jt}^J$ as total investment cost in period t based on a_t.

- $NPV_t^{CPM(B)}$ as the NPV in period t of the capacity project for $\boldsymbol{A}_t^{(B),*}$ determined by the CPM-LCM or the 2SP (B), respectively, based on forecasting realizations $\boldsymbol{d}_t$, decision history $\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1})$:

$$NPV_t^{CPM(B)}\big(\boldsymbol{A}_t^{(B),*}\big|\boldsymbol{d}_t, \hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1})\big)$$
$$= -v_t(a_t^{(B),*}) - \sum_{d_{t+1} \in D} \pi_t(d_{t+1})\beta v_{t+1}\big(a_{t+1}^{(B),*}(d_{t+1})\big)$$
$$- \sum_{d_{t+1} \in D} \sum_{d_{t+2} \in D} \pi_t(d_{t+1})\pi_{t+1}(d_{t+2})\beta^2 v_{t+2}\big(a_{t+2}^{(B),*}(d_{t+1}, d_{t+2})\big)$$
$$- ...$$
$$- \sum_{d_{t+1} \in D} ... \sum_{d_{|T|-1} \in D} \pi_t(d_{t+1})...\pi_{|T|-2}(d_{|T|-1})\beta^{|T|-t-1} v_{|T|-1}\big(a_{|T|-1}^{(B),*}(d_{t+1}, ..., d_{|T|-1})\big)$$
$$+ \sum_{d_{t+1} \in D} ... \sum_{d_{|T|} \in D} \pi_t(d_{t+1})...\pi_{|T|-1}(d_{|T|})\beta^{|T|-t} NPV^{LCM}\big(\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}), \boldsymbol{A}_t^{(B),*}, d_{|T|}\big)$$

$$(A.58)$$

- $\tilde{a}^{(B),\tau}$ as stage τ decision in an optimization run of the CPM-LCM or the 2SP (B), respectively. Furthermore, we assume $NPV_0^B \neq 0$ and $|A| > 1$.

To proof the superiority of the CPM-LCM, we require the property established by Lemma A.1. It states that, assuming the same decision history up to period t, if the optimal decisions determined by the CPM-LCM and by the 2SP in period t are not the same, the NPV for the remaining periods resulting from the CPM-LCM is always greater or equal to the NPV resulting from the 2SP.

Lemma A.1. *For $\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}) = \hat{\boldsymbol{a}}_{t-1}^B(\boldsymbol{d}_{t-1})$, $NPV_t\big(\boldsymbol{A}_t^*(\boldsymbol{d}_t)\big) \geq NPV_t^B\big(\boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t)\big)$ for all configuration trees $\boldsymbol{A}_t^*(\boldsymbol{d}_t), \boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t)$ with $a_t^*(\boldsymbol{d}_t) \neq a_t^{B,*}(\boldsymbol{d}_t)$ in period t of the capacity planning project.*

Proof of Lemma A.1. We conduct a proof by contradiction. Assume,

$$\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}) = \hat{\boldsymbol{a}}_{t-1}^B(\boldsymbol{d}_{t-1}),$$

$$a_t^*(\boldsymbol{d}_t) \neq a_t^{B,*}(\boldsymbol{d}_t), \tag{A.59}$$

$$\text{and } NPV_t^{CPM}\big(\boldsymbol{A}_t^*(\boldsymbol{d}_t)\big) < NPV_t^B\big(\boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t)\big). \tag{A.60}$$

Then, $a_t^{B,*} = \tilde{a}^{B,1,*}$ is the optimal stage 1 decision in $\big(\tilde{a}^{B,1,*}, \tilde{a}^{B,2,*}(d_{t+1})\big)$ determined by the 2SP applied in period t of the rolling horizon scheme and $a_t^* = \tilde{a}^{1,*}$ is the optimal decision determined by the CPM-LCM with

$$\tilde{a}^{1,*} = \arg\max_{\tilde{a}^1 \in A}\big\{V_t\big(\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}), \boldsymbol{d}_t\big)\big\}$$
$$= \arg\max_{\tilde{a}^1 \in A}\Big\{ -v_t(\tilde{a}^1) + \beta \sum_{d_{t+1} \in D} \pi_t(d_{t+1})V_{t+1}\big(\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}), \tilde{a}^1, \boldsymbol{d}_t, d_{t+1}\big)\Big\}. \tag{A.61}$$

Applying the Bellman principle, (A.61) can be rewritten as

$$\tilde{a}^{1,*} = \arg \max_{\tilde{a}^1 \in A} \Bigg\{ - v_t(\tilde{a}^1)$$

$$+ \beta \sum_{d_{t+1} \in D} \pi_t(d_{t+1}) \Bigg[- v_{t+1}\big(\tilde{a}^{2,*}(d_{t+1}, \tilde{a}^1)\big) + \beta \sum_{d_{t+2} \in D} \pi_{t+1}(d_{t+2}) \Big[...$$

$$+ \beta \sum_{d_{|T|-1} \in D} \pi_{|T|-2}(d_{|T|-1}) \Big[- v_{|T|-1}\big(\tilde{a}^{|T|-t,*}(d_{t+1}, ..., d_{|T|-1}, \tilde{a}^1)\big)$$

$$+ \beta \sum_{d_{|T|} \in D} \pi_{|T|-1}(d_{|T|}) NPV^{LCM}\big(\hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1}), \tilde{a}^1, \tilde{a}^{2,*}(d_{t+1}), ..., \tilde{a}^{|T|-t,*}(d_{|T|-1}), d_{|T|}\big) \Big] \Big] \Bigg] \Bigg\},$$

where $\tilde{a}^{2,*}(d_{t+1}, \tilde{a}^1), ..., \tilde{a}^{|T|-t,*}(d_{t+1}, ..., d_{|T|-1}, \tilde{a}^1)$ are the optimal decisions based on the backwards recursion of the dynamic program. Thus,

$$\tilde{a}^{1,*} = \arg \max_{\tilde{a}^1 \in A} \Big\{ V_t\big(\tilde{a}^1, \tilde{a}^{2,*}(d_{t+1}, \tilde{a}^1), ..., \tilde{a}^{|T|-t,*}(d_{t+1}, ..., d_{|T|-1}, \tilde{a}^1) \big| \boldsymbol{d}_t, \hat{\boldsymbol{a}}_{t-1}(\boldsymbol{d}_{t-1})\big) \Big\}$$

$$\Leftrightarrow V_t(\tilde{a}^{1,*}) = \max_{a_t \in A}\{V_t(a_t)\} = NPV_t^{CPM}\big(\boldsymbol{A}_t^*(\boldsymbol{d}_t)\big)$$

$$\overset{(A.59)}{\Leftrightarrow} \quad \tilde{a}^{1,*} \neq \tilde{a}^{B,1,*} \quad \wedge \quad NPV_t^{CPM}\big(\boldsymbol{A}_t^*(\boldsymbol{d}_t)\big) \geq NPV_t^B\big(\boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t)\big),$$

which is a contradiction to the original assumption (A.60). Thus, $NPV_t^{CPM}\big(\boldsymbol{A}_t^*(\boldsymbol{d}_t)\big) \geq NPV_t^B\big(\boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t)\big) \ \forall \boldsymbol{A}_t^*(\boldsymbol{d}_t), \boldsymbol{A}_t^{B,*}(\boldsymbol{d}_t) \ni a_t^*(\boldsymbol{d}_t) \neq a_t^{B,*}(\boldsymbol{d}_t)$. □

Now, we are able to proof the superiority of the CPM-LCM stated by Proposition 4.1.

Proof of Proposition 4.1. We conduct a proof by contradiction. It is sufficient to show

$$\omega \geq 0 \ \forall \boldsymbol{A}_0^*, \boldsymbol{A}_0^{B,*} \quad \Leftrightarrow \quad NPV_0^{CPM}(\boldsymbol{A}_0^*) \geq NPV_0^B(\boldsymbol{A}_0^{B,*}) \ \forall \boldsymbol{A}_0^*, \boldsymbol{A}_0^{B,*}$$

$$\Leftrightarrow \quad \nexists NPV_0^{CPM}(\boldsymbol{A}_0^*) < NPV_0^B(\boldsymbol{A}_0^{B,*}).$$

Assume,

$$\exists NPV_0^{CPM}(\boldsymbol{A}_0^*) < NPV_0^B(\boldsymbol{A}_0^{B,*}) \tag{A.62}$$

$$\overset{(A.58)}{\Rightarrow} \quad \boldsymbol{A}_0^* \neq \boldsymbol{A}_0^{B,*} \quad \Leftrightarrow \quad \exists t \in T \ni a_t^*(\boldsymbol{d}_t) \neq a_t^{B,*}(\boldsymbol{d}_t) \quad \wedge \quad \hat{\boldsymbol{a}}_{t-1}^*(\boldsymbol{d}_{t-1}) = \hat{\boldsymbol{a}}_{t-1}^{B,*}(\boldsymbol{d}_{t-1})$$

Applying Lemma A.1,

$$NPV_t^{CPM}\big(a_t^*(\boldsymbol{d}_t)\big) \geq NPV_t^B\big(a_t^{B,*}(\boldsymbol{d}_t)\big)$$

$$\overset{(A.58)}{\Rightarrow} \quad NPV_0^{CPM}(\boldsymbol{A}_0^*) \geq NPV_0^B(\boldsymbol{A}_0^{B,*}) \; \forall \boldsymbol{A}_0^*, \boldsymbol{A}_0^{B,*},$$

which is a contradiction to the original assumption in (A.62). Thus, $\omega \geq 0 \; \forall \boldsymbol{A}_0^*, \boldsymbol{A}_0^{B,*}$.

$\square$

Appendix B.

Chapter 5

B.1. List of symbols in the dynamic platform planning model

In the following, all symbols are listed that are used in the the dynamic platform planning model presented in Section 5.3 and Appendix B.2.

Index sets

$m \in M$	Set of products assigned to focal platform.
$t \in \{0, 1, ..., T-1\}$	Set of periods for *platform launch* with horizon T.

Variables

$x_t \in \{0, 1\}$	Decision variable: 1, if platform is launched in period t; 0, otherwise.
$z_t \in \{0, 1, 2, ...\}$	State variable: Level of technological innovation in period t.
$\zeta_t \in \{0, 1, 2, ...\}$	Random variable: Incremental level of technological innovation in period t with distribution ϕ.

Parameters

$\alpha \geq 1$	Growth rate for incremental development costs for expediting product development.
$\beta \in [0,1]$	Discount factor.
$\gamma(z) \geq 0$	Incremental profit per unit due to scale economies of platform with innovation level z.
$\delta_m(z) \geq 0$	Innovation-sensitive demand ratio of product m with innovation level z.
$\epsilon \in [0,1]$	Learning parameter of learning curve underlying the scale economies.
$\eta_m > 0$	Demand magnitude of product m.
$\vartheta > 0$	Total development costs assuming nominal development time λ.
$\vartheta^M > 0$	Development cost of one product.
$\kappa \geq 0$	Incremental development costs (penalty) for expediting the product development by one period.
$\lambda \in \{1,2,...\}$	Nominal development time of a product in periods.
$\xi_m \in [0,1]$	Demand growth rate of product m.
$\pi_m \in \mathbb{R}$	Profit per unit of product m.
$\rho \in [0,1]$	Extent of platform savings in development costs.
$\sigma \in \{1,2,...\}$	Product lifecycle length in periods.
$\tau_m \in \{1,...,T-1\}$	Period of SOP of product m.
$\omega > 0$	Platform-related unit costs.

Functions

$D_t \geq 0$	Total development costs, if platform is launched in period t.
$H_t \in \mathbb{R}$	Profit-to-go, if platform is not launched in period t.
$I_t \in \mathbb{R}$	Profit-to-go, if platform is launched in period t.
$P_{mt} \in \mathbb{R}$	Lifecycle profit of product m, if platform is launched in period t.
$V_t \in \mathbb{R}$	Value function of MDP in period t.

B.2. Implementation of platform cost benefits

Scale economies

In our experiments, we consider scale economies based on the concept of the learning curve with learning parameter $\epsilon \in [0,1]$ and platform-related unit costs ω (cf. Yelle,

1979). Note that the learning parameter corresponds to a learning rate of $1 - 2^{-\epsilon}$, which describes the percentage of reduction in unit costs as the cumulative production volume doubles. The platform-related unit costs ω are the unit costs generated by processes or parts that are standardized by the platform.

Therefore, the platform-related unit costs can be expressed as

$$\frac{1}{\delta(z_t)} \sum_{\delta'=1}^{\delta(z_t)} \omega(\delta')^{-\epsilon}, \tag{B.1}$$

where δ is the cumulative platform volume $\delta(z_t) = \sigma \sum_{m \in M} \delta_m(z_t)$, given the platform is launched in period t.

Based on Expression B.1 the incremental profit due to scale economies can be computed as follows:

$$\gamma(z_t) = \omega \left[1 - \frac{1}{\delta(z_t)} \sum_{\delta'=1}^{\delta(z_t)} (\delta')^{-\epsilon} \right]. \tag{B.2}$$

γ is precomputed for every feasible z_t and given as input for the dynamic program described in Section 5.3.

To compute the (reduced) scale economies in the case of the non-platform approach, we apply Equation (B.2) separately for every product m by setting $\delta(z_t) = \sigma \delta_m(z_t)$ as the cumulative volume of product m, given the individual development project of product m is launched in period t.

Scope economies

In our experiments, we consider scope economies based on the regular development costs for one product and simplified process steps in the individual product development projects (cf. Krishnan et al., 1999). ϑ^M denotes to the regular development costs for one product. $\rho \in [0, 1]$ describes the extent of platform savings in development costs compared to the total regular development costs without platforming (i.e. $|M|\vartheta^M$).

We set ϑ to $(1 - \rho)\vartheta^M|M|$. Furthermore, we express the penalty costs for one period of expedited development κ as regular development costs per product and period, i.e. $\kappa = \frac{(1-\rho)\vartheta^M}{\lambda}$. Consequently, the time-sensitive development costs, given the platform is launched in period $t < \min\{\tau_m\}$, can be expressed as follows, where $y = [\lambda - (\tau_m - t)]^+$

and $[u]^+ = \max\{u, 0\}$:

$$D_t = (1 - \rho)\vartheta^M \left(|M| + \sum_{m \in M} \frac{[y]^\alpha_-}{\lambda} \right). \tag{B.3}$$