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Production and capacity planning methods for flexible and reconfigurable assembly systems

PhD Thesis

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"Scientists discover the world that exists; engineers create the world that never was."

Theodore von Kármán,
aerospace engineer (1957)

Declaration

Herewith I confirm that all of the research described in this dissertation is my own original work and expressed in my own words. Any use made within it of works of other authors in any form, e.g., ideas, figures, text, tables, are properly indicated through the application of citations and references.

Budapest, April 4, 2018

Dávid Gyulai

Nyilatkozat

Alulírott Gyulai Dávid kijelentem, hogy ezt a doktori értekezést magam készítettem és abban csak a megadott forrásokat használtam fel. Minden olyan részt, amelyet szó szerint, vagy azonos tartalomban, de átfogalmazva más forrásból átvettem, egyértelműen, a forrás megadásával megjelöltem.

Budapest, 2018. április 4.

Gyulai Dávid

Abstract

The increasing diversity of product portfolios and difficult predictability of customer order streams introduce new, complex challenges in production management, as companies often need to apply special, advanced capacity and production planning methods to achieve and keep the desired level of internal efficiency. In case a company offers a diverse —regarding both volume and mix— product portfolio, the commonly applied production system structures are often inflexible to provide cost-efficient operation in the different stages of products' lifecycles.

The thesis introduces new models and methods to solve production and capacity planning problems, focusing on assembly systems, and utilizing the advantages of different system structures and resource types (dedicated, flexible, reconfigurable). The primary aim of the presented research is to define and elaborate new planning methods that support matching production capacities with the order stream on each level (strategic, tactical, operational) of the planning hierarchy, even in case a diverse product portfolio is to be managed. The methods are capable of considering the external, and also the internal, technology-related factors and constraints to achieve cost-efficient production.

Chapter 1 defines the topic of the thesis, and the motivation of the research. In Chapter 2, a literature review is provided with an introduction of relevant, state-of-the-art methods. Chapter 3 introduces a new, hierarchical capacity management framework, focusing on modular assembly systems, and providing cost-efficient production plans on each level of the planning hierarchy. The models of the framework are primarily defined so as to meet the requirements of manual assembly systems, and utilize their scalability achieved via changing the amount of allocated human labor, or the number of applied modules. Chapter 4 discusses the capacity management of reconfigurable, robotic assembly cells, and introduces a new method that is aimed at supporting the design and management of cells by combining the application of mathematical and simulation models. Chapter 5 focuses on robust production and capacity planning, related to manually operated flexible assembly lines. A new, simulation-based optimization method is presented, which utilizes quasi-real-time data to represent the actual status of the production system, and to project its future expected behavior, based on realistic production scenarios. In this way, information about the actual capacity requirements is obtained, and used in mathematical models to calculate robust plans in a proactive way. Chapter 6 summarizes the results presented in the dissertation, and introduces the methods' application in practice.

Kivonat

A vevői megrendelések napjainkban tapasztalható, a korábbiaknál is nehezebb előrejelezhetősége, illetve az összetett termékportfóliók kezelése komoly kihívásokat jelentenek a termelő vállalatok számára, a termékek költséghatékony gyártása ugyanis új, speciális kapacitás- és termeléstervezési módszereket igényel. Amennyiben egy cég változatos termékválasztékkal rendelkezik, az ipari gyakorlatban általánosan elterjedt gyártórendszer struktúrák nem minden esetben kellően rugalmasak ahhoz, hogy biztosítsák a gazdaságos termelést a termékek életciklusának különböző fázisaiban.

Az értekezés olyan új módszereket mutat be, amelyek szerelőrendszerekkel kapcsolatos termelés- és kapacitástervezési problémákra nyújtanak költséghatékony megoldást, kihasználva a különböző struktúrájú erőforrások (dedikált, rugalmas, újrakonfigurálható) nyújtotta előnyöket. A kutatómunka során az elsődleges célom olyan kapacitástervezési módszerek kidolgozása volt, melyek a tervezési hierarchia minden szintjén, vagyis hosszú- (stratégiai), közép- (taktikai) és rövidtávon (operatív szint) is hatékonyan képesek összehangolni a termelési folyamatokat a változó vevői igényekkel széles termékválaszték esetén is, ennek megfelelően olyan modelleket vizsgáltam, amelyek képesek biztosítani a költséghatékony termelést a belső (technológiai) és külső (vevői) korlátozások figyelembevétele mellett.

Az értekezés első fejezete (Chapter 1) ismerteti a kutatási témát, valamint a kutatás motivációját. A második fejezet (Chapter 2) célja a kapcsolódó szakirodalom bemutatása, valamint a releváns *state-of-the-art* megoldások ismertetése. A harmadik fejezet (Chapter 3) egy új, többszintű tervezési keretrendszert mutat be, amely a tervezési hierarchia mindhárom szintjén költséghatékony terveket szolgáltat moduláris felépítésű szerelőrendszerek számára. A modellek elsősorban kézi szerelőrendszerek termeléstervezését szolgálják, kihasználva azt az előnyös tulajdonságot, miszerint az ilyen rendszerekben a kézi és gépi kapacitások egyaránt viszonylag rugalmasan változtathatók. A negyedik fejezet (Chapter 4) az újrakonfigurálható, robotizált szerelőrendszerek kapacitásmenedzsmentjét tárgyalja, ismertetve egy olyan új módszert, amely a rendszerek költséghatékony tervezését és üzemeltetését biztosítja, különböző új matematikai és szimulációs modellek alkalmazása révén. Az ötödik fejezet (Chapter 5) manuális, kézi szerelősorok robusztus termelés- és kapacitástervezésével foglalkozik. Egy olyan új, szimulációs optimalizáláson alapuló módszert dolgoztam ki, ahol a rendszer aktuális állapotát tükröző közel-valósidejű adatok szolgáltatják a szimulációs modell paramétereit, a szimulációs vizsgálatok pedig különböző virtuális, de realisztikus termelési szcenáriók alapján vetítik előre a rendszer jövőben várható viselkedését. A szimulációs vizsgálat eredményeként egy olyan adathalmazhoz jutunk, amely tartalmazza a különböző gyártási sorozatokhoz tartozó kapacitásigényeket a sztochasztikus paraméterek figyelembevétele mellett, ezáltal proaktív módon támogatja robusztus tervek számítását. A hatodik fejezet (Chapter 6) összefoglalja a dolgozatban bemutatott új tudományos eredményeket, módszereket, valamint azok gyakorlati alkalmazását.

Acknowledgments

Although the thesis is submitted under my name as an author, several colleagues and friends supported me during the past years to be able to finalize this work. I would like to highlight that the research presented in the thesis covers various segments of the broad field of engineering, therefore, I feel myself lucky that I could work in very good project teams, and real experts guided and helped me.

First, of all, I would like to express my gratitude to every person who directly supported the preparation of my thesis. At the first place, I am indebted to my supervisor Prof. László Monostori for supporting me with his advices, and providing me a stable working environment as an institute leader. Besides, of course, I am glad that I could hear a lot of his interesting and funny stories during the past years.

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Contents

Chapter 1

Introduction

1.1 Paradigm shifts and evolution of manufacturing systems

Manufacturing systems have continuously evolved over time together with changes of market trends and technological advances: one can observe that paradigm shifts in production were always triggered by great innovations, referred to as industrial revolutions, and had great impacts on both society and economy. The first industrial revolution started by the mechanization, and the invention of water steam power, and manifested in the craft production with general purpose machine tools during the 19th century. At that times, markets were characterized by tailored products with high variety and low volume, and production was pulled by the individuals' needs. The golden era of inventions led to the second revolution with the first conveyor belt and assembly line. They made the mass production possible, best exemplified by Ford's *dedicated manufacturing line*, capable of producing a single car model (Womack et al., 1990). In parallel, the business model was also changed drastically, with the objective of satisfying the mass' needs with low variety of products hailed to the market following push strategy. The needs for higher level of automation, slightly greater product variety, increased efficiency and the advance of information technology led together to the third industrial revolution with the first programmable logic controller, and the corresponding *flexible manufacturing lines* developed first in the middle of the 20th century. The flexible production paradigm still offers one of the most efficient solutions for producing variety of products in a cost-efficient, automated way, applying advanced production management tools and techniques. Right production management decisions and the corresponding support tools are mostly requested by the transformation of market needs, demanding to turn the push strategy into pull again when customers can select the product from various types to be delivered by a certain due date. As a result, the recent trend in production management is that companies are put under pressure by competitive markets and by facing several challenges arising from the management of a great variety of products with shortening lifecycles and customer-expected lead times. As a possible response from the production side, smart tools and techniques are integrated in the products and production systems via information-communication solutions, resulting in cyber-physical production systems (CPPS) as the flagships of recent technological changes, often referred to as the fourth industrial revolution or *Industry 4.0* (Monostori et al., 2016). Although *reconfigurable and modular system* paradigms were present before this era (Koren et al., 1999), they became fundamental means of CPPSs, as they are capable of producing a great variety of products by the changeable structure, functionality and scalable capacity (ElMaraghy, 2005). Moreover, the structural advantages of

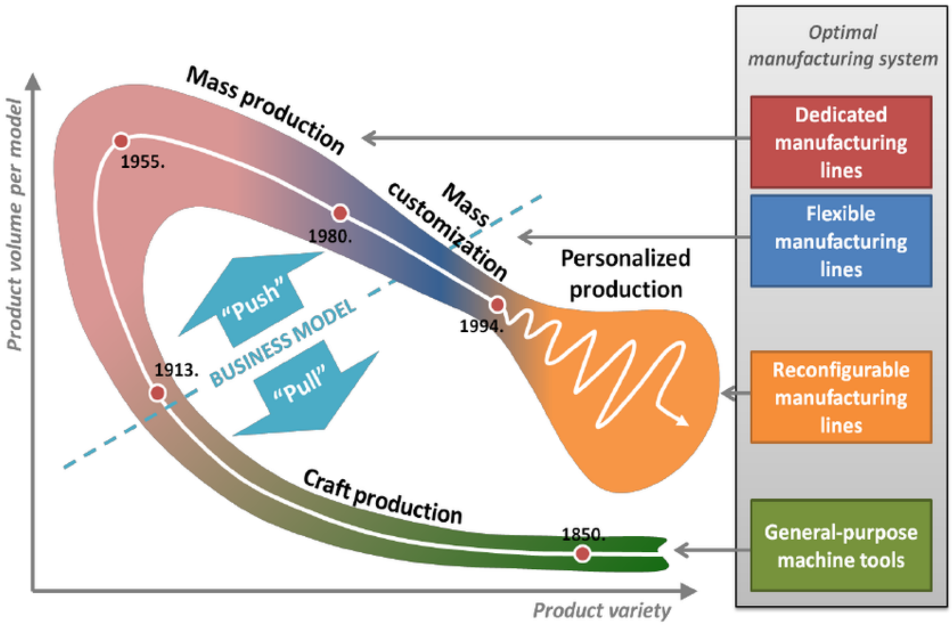


Figure 1.1. Paradigm shifts and the evolution of manufacturing systems according to Koren (2010).

these systems can be exploited more efficiently, if smart characteristics of products, processes and system elements are combined with the reconfigurable and modular capabilities (ElMaraghy and ElMaraghy, 2016). The above described paradigm shifts, business model changes and system evolution are represented by Figure 1.1.

Focusing on the recent situations in production, the ever-changing market requirements —regarding volume, mix and time dimensions— have significant impacts on the applied production system and strategy: the production systems have to follow the trends of products' lifecycle in order to maintain the *economies of scale*, meaning the balance between the expected throughput and the corresponding production costs. Besides, reaching the *economies of scope* is also desired to keep the costs on the lowest possible level, even though a great variety of products need to be produced. Therefore, the *coordinated evolution (co-evolution)* of products, processes, and production systems is required to continuously revise and maintain the system configuration, in order to withstand the disadvantageous effects of the external drivers (Tolio et al., 2010). These requirements are valid for both production and assembly systems. As for the major difference between them, it can be generally said that *manufacturing systems* convert raw materials into components, while *assembly systems* convert raw materials and components into functional products (Owen, 2013). Assembly often constitutes the last stage of a discrete manufacturing process and the accumulated processing value of the product is high, compared to other manufacturing processes at previous stages (as cited by Bi et al. (2007)).

Focusing on the management of assembly systems, the aforementioned important business goals can be achieved by utilizing the modularity of products as well as the flexibility of the applied assembly systems (Bryan et al., 2007). This can be done by reducing the variant-dependent components in the systems, and applying systems that are built up of universal modules (Lotter and Wiendahl, 2009). Flexible and reconfigurable assembly systems can support the firms to fulfill the customer needs while keeping the costs on the lowest possible level, even in a turbulent market (Westkämper, 2003). These system types and the aforementioned enablers are essential

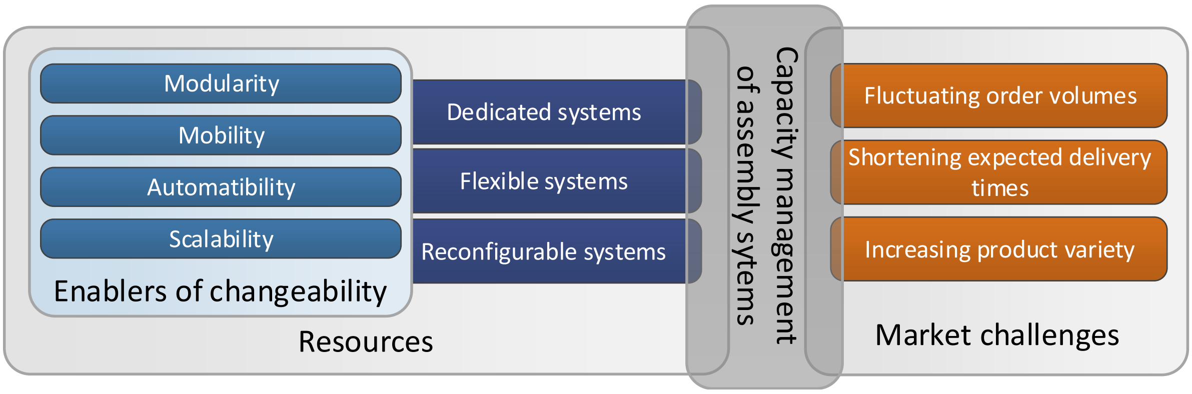


Figure 1.2. Map of concepts for capacity management of assembly systems: matching internal resources with market needs, considering the heterogeneity of systems based on the enablers of changeability.

elements of changeable manufacturing that is defined as the characteristic to accomplish early and foresighted adjustments of the factory's structures and processes on all levels, due to change impulses, economically (ElMaraghy and Wiendahl, 2009). On Figure 1.2, the role of capacity management of assembly systems is highlighted, in case different system types are considered that utilize different enablers of changeability as defined by Wiendahl et al. (2007). Accordingly, the advantages of these systems can be exploited only if the right balance among the different capacities is found. Considering the design of assembly systems, an important task is to find the most appropriate system configuration that provides the desired production rate on the lowest possible cost (Hu et al., 2011). Special, yet well-known problems in assembly technology are *sequence planning* and *line balancing*, both supporting the detailed *configuration* of assembly lines and systems. Assembly sequence planning determines the sequences of tasks and sub assemblies according to the product design description (Rashid et al., 2012), whereas line balancing matches tasks and physical workstations considering a given line shape (e.g. U-shape or parallel line) (Becker and Scholl, 2006). These methods provide the basis for the periodic capacity management and production planning in relation with assembly systems. From this perspective, there is an obvious need for efficient *production planning and control* methods that support the application of flexible and reconfigurable systems (ElMaraghy et al., 2012a). Important factor in the capacity management of assembly systems is the role of human labor, as processes are often completely or partly manual. The output rate of these systems can be adjusted through the allocated manpower, therefore, manual labor capacity needs to be always in balance with the applied production plan and system configuration. Essential characteristics of the human labor is the flexibility, regarding the skills of operators that can be widened by training programs. Combining this enabler of the *"Operator 4.0"* concept (Romero et al., 2016) with the modular architecture and smart IT technologies of cyber-physical assembly systems, great opportunities can be identified to support efficient product variety management.

1.2 Motivation

Concerning the above thoughts, the motivation of research is derived from the fact that capacity management methods focusing on modular assembly systems got little scientific attention so far, as discussed in detail in Chapter 2. However, assembly is an essential part of the total manufacturing, as the costs related to assembly are typically 25% to 50% of the total cost of manufacturing, moreover, the percentage of workers involved in assembly operations ranges from 20% to 60%. Within the research, assembly systems will be analyzed, in which operations involve alignment, orientation of components as well as their physical attachment by joining processes. The objective is to define capacity management methods that match the system structure and operations with the order stream, considering the volatile nature of the latter. The portfolio of the assembled products is diverse regarding the assembly process steps as well as the order volumes of products. The methods aimed at supporting the capacity management related tasks on each level of the classical planning hierarchy, thus short, medium and long term decisions are all considered. When planning the capacities and production, the actual configuration of the assembly system —including the modules from various types— always needs to be taken into consideration. As discussed later in Chapter 2, assembly systems with heterogeneous resources are mainly considered, where dedicated, flexible and reconfigurable resources constitute the overall configuration. These resource types entail different investment and operation costs that are of crucial importance when deciding about the applied configuration on the long term, and assigning the products to resources. On the medium and short terms, the emphasis is put on the dynamic operation of the reconfigurable and flexible systems, ask for special capacity planning methods that handles the changeable system structure and variability of time and quality related parameters, resulted by the human factor.

All in all, cooperative decision support methods and models are to be developed, with the objective of minimizing the overall costs, related to the application of assembly systems in a changeable environment, where customer order stream changes over time, as well as the product variety is great. The methods need to be applicable in real industrial environment characterized with the above factors, therefore, their practical usability is desired.

1.3 Outline of the dissertation

The results presented in the dissertation are concentrated around two main topics, briefly characterized in the previous sections. First part of the work introduces novel results achieved in the *capacity management of modular assembly systems*, providing new models and methods in each levels of the planning hierarchy (detailed in Section 2.1). In the second part, the emphasis is put on the *robust production planning* methods for flexible assembly lines, where the variability of actual workload is significant, increasing the complexity of daily production planning activities. All of the presented methods are demonstrated through real use cases from the industry. The dissertation is outlined in the following paragraphs, and an overview about the structure and results is provided in Figure 1.3, depicting the different methods with the corresponding planning level(s) and system types. Besides referring to the chapter that presents a given method, the related thesis statements that summarize the new scientific results are also referred (the thesis statements are summarized in Chapter 6.1).

First, a literature review is provided in Chapter 2, presenting the state-of-the-art techniques in product variety management, modular assembly systems, and robust production planning. The reader can identify that the increased variety of products entails complex tasks in the operations management, therefore, innovative solutions are needed to efficiently cope with the changes in the volume and mix of the products. Modularization of assembly systems including flexible and reconfigurable ones offers a reasonable solution to produce products in a great

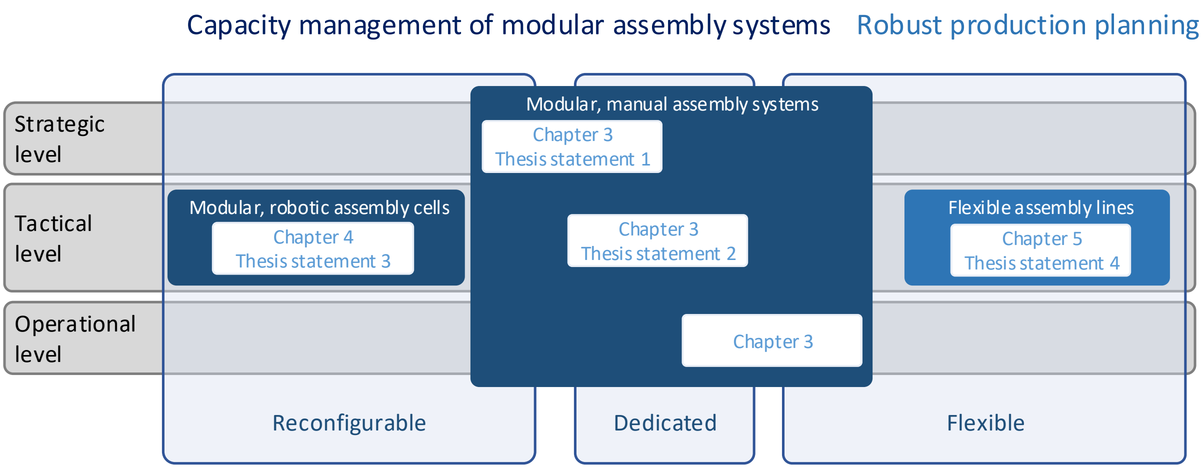


Figure 1.3. Overview of the topics and results presented in the dissertation, in relation with the planning levels and focused system types.

variety, however, there is a lack of suitable capacity management methods applicable for these special system structures.

In Chapter 3, a novel method is presented for the management of product variety in assembly systems, by applying a new framework developed to enable the periodic revision of the capacity allocation and the system configuration. The substantial contribution and novelty of the method is realized in the approximation of the costs —including cost factors affected by the dynamic reconfiguration processes— by prediction models that are applied in optimization models supporting higher level configuration decisions. Moreover, nonlinear interactions among the assembly processes of different products are also tackled by introducing dummy decision variables (product subsets are determined with statistical models), supporting to keep the linearity of the models while capturing the underlying interactions among the processes. In order to evaluate the reliability of this approximation scheme in portfolio-based decisions, a simplified, product-based version of the system configuration problem, called line assignment is solved first as a proof-of-the-concept. Thereafter, the framework is presented providing capacity management related solutions for each level of the classical planning hierarchy, which is introduced in Section 2.1. On the higher level, a system configuration problem is solved to assign the product families to dedicated, flexible or reconfigurable resources, considering dynamic factors like uncertain order volumes. At the lower level of the hierarchy, it ensures the cost efficient production of the system by optimizing the lot sizes as well as the required number of modules corresponding to the calculated plan.

In Chapter 4, the scope of the analysis is shifted from manual assembly systems to modular, robotized assembly cells. A new design and management framework is defined for the cost-efficient management of these cells throughout their life, integrating multiple interlinked tools. The framework is developed within a collaborative research: in the dissertation, the own part of this work is highlighted as a new scientific result, namely the so-called *Production Planning and Simulation Tool*. In the method, the planning and simulation models are responsible for calculating the future expected operation costs, considering the tactical level factors already in the early design stage of the cells. Besides, the predicted production lot sizes are also estimated, supporting the dynamic performance evaluation of various cell configurations.

In Chapter 5, a novel planning method is introduced with the essence of combining shop-floor data from the *manufacturing execution system (MES)*, and higher level data from the *enterprise resource planning (ERP)* systems, facilitating the calculation of robust production plans. The method combines data analytics techniques and discrete-event simulation in the mathematical model of production planning and scheduling. It can be achieved by utilizing sensor-level data in production planning in a proactive way, with the objective of decreasing the overall production costs while being robust against the disturbances that might worsen the performance of the plan. Thanks to the latest process monitoring techniques and technology applied in CPPSs, diverse, and more detailed data can be gathered from the shop-floor than ever before, supporting to capture the effects of human factor on the quality and time related parameters, applying statistical models. In this way, the negative effects can be eliminated by calculating robust plans: in contrast to most, iterative simulation-based optimization techniques, the presented method relies on linear regression models, thus requires less computation efforts. Compared to the existing robust optimization and iterative simulation-based techniques, the method proposed in the dissertation results in less lateness on lower costs (cost of robustness), while keeping the simplicity and thus short running time of the planning algorithms, enabling to apply it in real industrial environment, as presented by a case study from the automotive sector.

Chapter 2

Literature review

The recent challenges in operation management were presented in the previous chapter, highlighting that today's production is mainly characterized with ever increasing complexity in the customer needs, manifested mainly in the turbulence of markets, uncertainty and variety of the prices and order volumes (ElMaraghy et al., 2012b). Although companies are under pressure of the market needs and influenced by the market trends, some state-of-the-art approaches, including production system paradigms, as well as the complementary management methods offer reasonable solutions to tackle these requirements. In the followings, concepts and tools of product variety management are introduced, emphasizing the solutions that are appropriate for assembly systems. The literature review highlights the research fields related to the sub-topics of the thesis, including the management of modular and changeable assembly systems, and the production planning approaches that aim to provide robust solutions for assembly lines. Additionally, state-of-the-art modeling techniques for operations management are introduced in Section 2.6.2, describing the tools and approaches that are used for optimization, data analytics and simulation throughout the thesis.

2.1 The role of planning in production

In production management, *planning* involves activities, processes, methods and techniques needed to take, make and account for customer orders, matching the internal processes with external market requirements (Schönsleben, 2016). According to Pinedo (2005), planning and scheduling functions in a company require mathematical techniques and heuristic methods, applied on a daily basis to achieve corporate business objectives. More specifically, planning determines the production activities to be performed in the upcoming periods, and the key tasks are the planning of production program, production requirements, the external procurements and the outbound deliveries (Lödding, 2012). Based on the previous thought, one can infer that production planning is a set of different activities, supporting decision in different phases, and on different stages of the production. Accordingly, Fleischmann et al. (2005) defined a *supply chain planning matrix*, categorizing the planning activities based on their resolution and time horizon (vertical axis) and the focused logistics area in the process chain (horizontal axis). In the planning matrix illustrated by Figure 2.1, the vertical axis depicts the three main stages of the planning hierarchy: the long-term strategic, the medium-term tactical, and the short-term operational planning. These categories are based on two, strongly correlated factors that are in inverse relation: the resolution (level of aggregation) and the time horizon of the planning

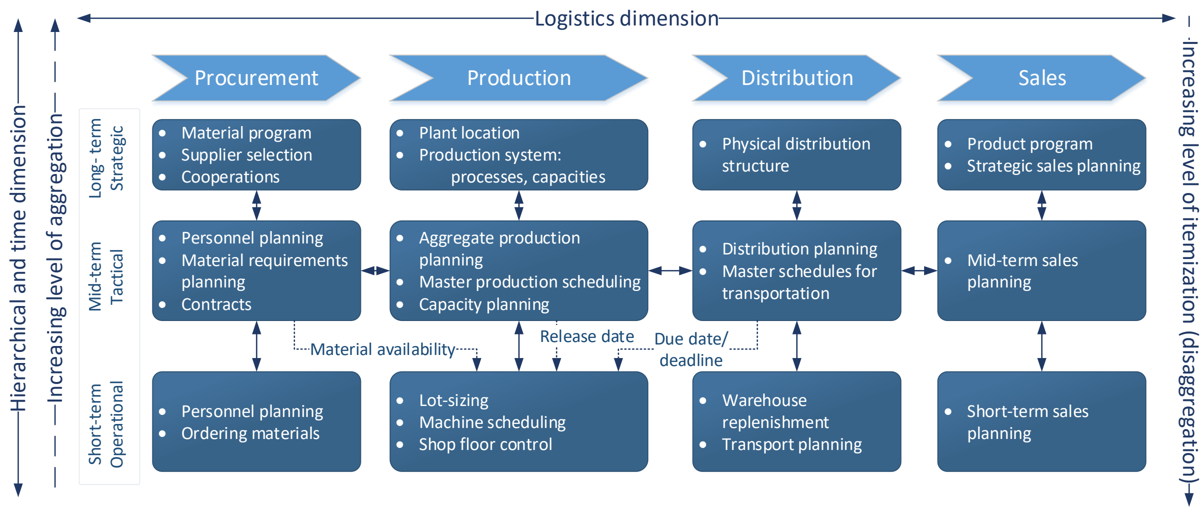


Figure 2.1. (Supply chain) planning matrix with tasks, according to Schönsleben (2016), modified from Fleischmann et al. (2005).

model. The reason for this is the uncertain and/or aggregate nature of the information, available about the future production scenarios on the long term, whereas on the operational level, typically a huge amount of information needs to be considered that increases the complexity of planning, therefore, it can be calculated only for the short upcoming term. One cannot draw clear boundaries between the different stages of the hierarchy, however, in practice, the term *planning* refers to tactical and strategic level activities, whereas *scheduling* corresponds to the operational level (Fleischmann et al., 2005). Although different tasks are solved in each stage of the hierarchy, they need to be consistent in a way that a higher level plan provides input to the lower level planning task, thus it needs to be feasible even if more details are considered when solving the lower level planning problems.

In general, *production planning* is responsible for matching the supply with demand, by balancing the internal capacities with the order stream, and transforming the customer needs into production orders, considering mainly the financial objectives (Pochet, 2001). The fundamental questions addressed in planning are: *What, when, how much and where to produce?* Besides, as planning is mostly performed on tactical and strategic levels, its time horizon is *bucketed* (consist of – usually equal length – time periods), and the operation sequences within the same time buckets are not preserved (big-bucket models). The time horizon and the corresponding resolution (period length) of planning mostly change in between a working shift and a year, depending on the corporate practice. As illustrated by Figure 2.1, production and capacity planning are hand-in-hand, due to the strong interdependencies among the constraints. As production planning always needs to consider the amount of available resources (material or labor), capacity and production are planned in an iterative or integrated way (Pochet and Wolsey, 2006). In the latter case, decision makers have the option of adjusting the amount of applied resources even on medium- or short-terms (e.g. overtime, or extra machine hours), in case the production requests for that (Kumar and Suresh, 2006; Russell and Taylor, 2011). Considering the strategic level decisions when a long time horizon is applied, plans often involve investment decisions about capacity expansions, or major changes in the applied resource set (Dal-Mas et al., 2011; Liu and Papageorgiou, 2013; Rastogi et al., 2011).

In contrast to planning, scheduling methods usually deal with a fine-granularity, bucketless time horizon, more specifically, tasks can be scheduled in practice even with a resolution of a minute. In scheduling, the most fundamental question to be answered is: *How to best to produce (sg.)?* This usually means the assignment of jobs to resources over time, and defining a sequence of jobs to be released, which task is influenced by priorities and constraints to be considered. In scheduling, the set of jobs to be sequenced, and the set of resources are usually given by the assembly process plans, and the emphasis is put on their proper assignment along time (Framinan et al., 2014). Operational level scheduling is in a close relationship with the execution and control of operations, therefore, continuous feedback is needed from the shop-floor to revise, and change the schedule (rescheduling) if needed, adjusting to the status of processes (Pfeiffer et al., 2007; Vieira et al., 2003).

2.2 Product variety management

Proper management of *product variety* is a recent challenge in operations management, involving several aspects from the design of the products to the coordination of the supply networks (ElMaraghy et al., 2013). In general, increased variety of today's product portfolios is originated from multiple root causes, among which the changes of production technology, applied materials and processes are of crucial importance. However, the main reason why firms are offering multiple variants for the customers relies on the competitiveness, more specifically that customers tend to buy products that either match their personal preferences, or the ones that can be customized easily. Even though the obvious advantage of mass customization is that products match better the requirements, variety is not necessarily good, both regarding the customers, as well as the companies' sides. On the one hand, customers are often confused about the differentiation of products variants (Huffman and Kahn, 1998), while on the other hand, companies need to manage the extra inventory, production and service costs entailed by the complex product portfolio. Focusing on the management issues of the product variety, the key of effectiveness relies on the application of flexible approaches regarding both the physical production system, as well as the corresponding planning and control layers.

Considering the challenges related to the system structure, the increasing number of variants and shortened product lifecycle[1] force companies to reduce the variant-dependent system components, as those cannot be cost-efficiently adapted to the changes (ElMaraghy and ElMaraghy, 2016; Lanza et al., 2010; Lotter and Wiendahl, 2009). As a reasonable solution, the application of flexible and reconfigurable assembly systems should be considered in order to reach the economies of scope (Fernandes et al., 2012). According to Wiendahl et al. (2007), flexibility and reconfigurability are specific to certain factory levels, therefore, the term changeability is introduced as an umbrella concept encompassing many aspects of change within an enterprise. State-of-the-art changeable systems are introduced in Section 2.3, emphasizing the concept of modularity applied in assembly systems. As for the planning and control layers of production, different approaches exist supporting the management of product variety by satisfying the customer needs as well as maintaining the internal efficiency. Regarding the changeability concept, the proper utilization of modularity in production and capacity planning is of crucial impor-

[1] Lifecycle of a product refers to the stages a product progresses through after its appearance in the market: introduction, growth, maturity and decline (Day, 1981). These stages reflect the sales volumes and thus production volumes, and typically represented as a function of time (lifecycle curve).

tance, as there are strong interdependencies among the costs that incur on the different layers of the planing matrix (Meyr et al., 2015). As highlighted by Colledani et al. (2016) and by Gyulai and Monostori (2017), if cost-efficient system configuration is desired, strategic decisions need to consider the costs that are mostly influenced by the strategic and operational level decisions. In this perspective, the related state-of-the-art techniques in system configuration and capacity management are presented in Section 2.4.

2.3 Modularity and changeability of assembly systems

Nowadays, changeability and flexibility are fundamental characteristics that can be utilized to meet challenges of the global market from the manufacturing systems' side. Tolio and Valente (2006) define flexibility as a characteristic of a system to change its behavior without changing its configuration, in contrast, changeability makes possible functional changes of a system via structural and configurational changes. In the management of assembly systems, (i) changeability and (ii) automatibility are fundamental enablers, and form the basis of different classification schemes. According to Wiendahl et al. (2007) (i) *changeability* makes possible the physical and logical objects of a factory to change their capability towards a predefined objective in a predefined time. In case of assembly systems, the enablers of changeability are *modularity, scalability, convertibility, mobility* and *automatibility*. Koren (2006) and ElMaraghy and Wiendahl (2009) define these elements as they follow. Modularity makes use of standardized resources as building blocks of the system, ensuring a high interchangeability with little cost or effort. Convertibility of changeable assembly systems is important to switch between product types rapidly, e.g. by utilizing adjustable fixtures and other resources. Scalability provides for spatial degrees of freedom, regarding expansion, growth and shrinkage of the factory layout. Mobility —as highlighted later— is important to reconfigure single stations or modules of an assembly system. As for the last enabler, the (ii) automatibility of assembly systems, three main levels of automation are distinguished: manual systems with human assemblers aided by simple tools, hybrid system where human workforce is supported by automated machines, and fully automated assembly systems. Conclusively, changeable assembly systems can have different levels of automation, however, the assembly costs depend both on the applied resources, and also on the desired level of reconfigurability (Wiendahl et al., 2007).

In changeable production technology three main paradigms are distinguished (Section 1.1), based on the structure, management, and focus of the applied resources: dedicated (DMS), flexible (FMS), and reconfigurable manufacturing systems (RMS) (ElMaraghy, 2005). Although these paradigms directly related to manufacturing systems, the same concepts exist in assembly technology, therefore, dedicated, flexible and reconfigurable assembly systems are also distinguished (Bi et al., 2007; Lotter and Wiendahl, 2009). *Dedicated assembly systems* are designed to produce a single product type in a high volume, with a fix line architecture. *Flexible assembly systems* also have fix structure in most cases, however, they are suitable for assembling a part family applying equipment with adjustable features including both software and hardware (Owen, 2013). *Reconfigurable assembly systems* have rapidly changeable capacity, as well as functionality applying convertible design to change the configuration when switching from one product type to another (Koren and Shpitalni, 2010).

From production management viewpoint, cost and time factors related to changeability are of crucial importance when configuring the systems, or deciding about the production plans.

Although there are neither definite boundaries nor specifications as a basis of categorization, dedicated systems are usually characterized by lower investment and higher production costs, whereas flexible systems have the opposite characteristics (Bruccoleri and Perrone, 2006). Reconfigurable systems are in between them by offering a reasonable solution with short changeover and reconfigurable times besides relatively low investment and operation costs. For the sake of comparability regarding the cost factors, the concept of *modularity* has been introduced as an umbrella, encompassing the building block resources of assembly systems that are of different classes in terms of changeability. Therefore, the *modular assembly systems* analyzed in the thesis can be either dedicated, flexible or reconfigurable ones, however, the modules have different capabilities, as well as their operation and investment entail in different costs. The analyzed systems consist of modular assembly lines that are designed to perform sequential assembly operations, and the structure of lines relies on the process-based alignment of assembly modules (Hu et al., 2011). These modules are the machine (non-human) *resources* of assembly systems that are considered to have finite capacities in the planning models introduced in the thesis. Besides their capacity, important characteristic of the modules is their capability, in this regard, one can distinguish among dedicated, flexible and reconfigurable assembly lines. Such mixed resource sets result in so-called *heterogeneous systems* include assembly lines that can be either dedicated, flexible or reconfigurable, according to the module types they are composed of. Although different lines constitute these heterogeneous systems, the module of a given line are from the same type. In order to characterize the different types of modules, some important concepts are clarified first, concerning the structure and operation of the system:

- *Modules* are the building blocks of modular assembly systems, capable of performing specific assembly tasks (e.g. screwing module, pressing module etc.). From structural viewpoint, one can distinguish among dedicated, flexible and reconfigurable modules. Modular design is a commonly applied technique for assembly systems, since it enables to build different system configurations from blocks with standardized features, often referred to as *"plug and produce"* modules (Onori et al., 2012; Wiendahl et al., 2007).

- *System configuration (noun)* refers to the architecture and selection of the modules from different types. Given a certain product, several configurations exist that are capable of realizing the product, however, in the high level-system configuration, exact alignment of the modules on the shop-floor is not considered, but only the main cost and performance indicators (investment cost, throughput, scalability and conversion time) when given module sets as configurations are evaluated. System configuration *(verb)* also refers to the activity when the system structure is defined, according to the above description.

- *Reconfiguration* refers to the procedure when the physical configuration of the assembly system is modified, e.g. the modules are realigned in order to build a new assembly line and produce different product.

Dedicated, flexible and reconfigurable paradigms have advantages and disadvantages, therefore, proper selection of modules and configuration of the system are of crucial importance towards the cost-efficient operation. Several papers compare the three paradigms of production systems, however, the rest of them concentrate mostly on manufacturing processes (Koren and Shpitalni, 2010; Lotter and Wiendahl, 2009; Zhang et al., 2006). The general characteristics summarized in the papers are valid for assembly systems as well, however, resources applied in assembly technology have some specific features as discussed below.

Dedicated assembly lines are designed for assembling a certain product in high volume that is relatively stable. Due to the inflexible design of the dedicated modules, they can be operated economically only if the production volumes remain high and relatively constant, as the redesign and ramp-up of a modified or new dedicated module often entail high costs. Dedicated lines are usually automated, and equipped with a conveying system, therefore, the required human labor content is relatively low.

Flexible assembly lines are capable of assembling different, but relatively similar products by the adjustment of fixtures and tools (e.g. changing the bit and adjusting the torque on a screwdriver). They consist of flexible modules that are designed for performing a specific assembly task (e.g. screwing) of more product types, that are assembled in a medium/higher volume that can slightly fluctuate over time. As flexible modules are fixed on the shop-floor, they do not enable physical reconfiguration, and the scalability of the system is very low. Some flexible lines are based on a hybrid assembly approach, where automated devices are combined with human labor, and the modules can be exchanged in a short time. Such modular systems are the combinations of flexible and reconfigurable ones, and suitable for quickly varying products and quantities, as the investment costs are lower than that of a highly automated system. Due to the higher level of flexibility, the risk of a bad investment is quite low (Wiendahl et al., 2007).

Reconfigurable assembly lines are capable of producing more product families, applying changeable fixtures and adjustable equipment. The modular structure enables to change the configuration of the system with relatively low efforts, and to scale up or down the capacity according to the order stream. When applying mobile, dockable workstations, the reconfiguration procedure can be shortened significantly, however, it is still longer than a simple setup on a flexible line. In contrast to the flexible systems that are suitable for assembling different parts in relatively constant volumes, reconfigurable lines offer adjustable flexibility and scalability (ElMaraghy and Manns, 2007; Meng, 2010). Utilizing these features, reconfigurable lines are usually applied for assembling products in the launch and end phases of their lifecycles (Koren, 2006).

Based on the above literature review of paradigms and system characteristics, a radar chart is sketched to visualize the main features of the different resource types, assigning higher scores to more advantageous characteristics (Figure 2.2). As introduced in the following sections, a system configuration is aimed to be determined, which combines the advantages of three separate system types, therefore, it has a heterogeneous structure. Concerning Figure 2.2, this would mean that the desired heterogeneous system configuration needs to cover the maximal possible area presented in the chart, by utilizing most of the benefits offered by the structure of the system.

2.4 Capacity management of assembly systems

In operations management, the general objective is to match supply with demand while minimizing the total incurring production costs that are inversely proportional with the internal efficiency, wish to be maximized. When considering several products and a dynamic market environment, this can be achieved by utilizing the flexibility and reconfigurability of the applied production resources, on each level of the planning hierarchy. Supplier companies, especially in the automotive industry, often face the challenge to introduce new products in their portfolio,

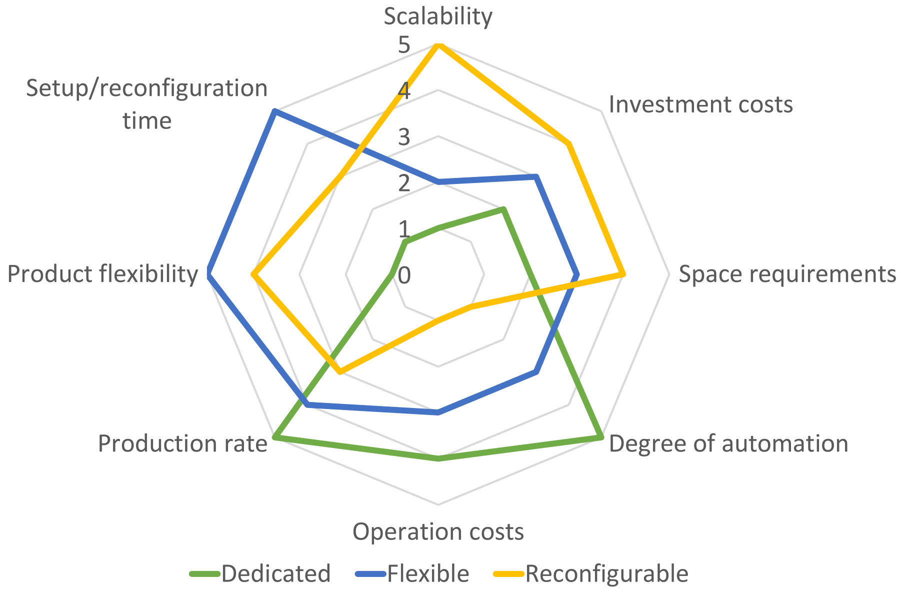


Figure 2.2. Radar chart with the features of different assembly system types.

because their customers also release new final products or modify the existing ones, requiring the modification of components. As markets are typically very competitive, quick responses to such challenges are required in order to keep customers and increase profit. Therefore, production managers and system designers have to find the right balance between throughput and production costs, utilizing the advantages of a proper system configuration with the complementary logical planning processes (ElMaraghy et al., 2012a). In this way, the changeability of systems can be increased, thus they can also accommodate to the changing product portfolio while the overall costs can be kept on a reasonable level (ElMaraghy and Wiendahl, 2009).

In case of modular assembly systems, capacity management means the long term investment strategy and product-resource assignment, and the goal is to minimize the costs that incur on the long run, while keeping the desired service level (Renzi et al., 2014). In the terminology, this field of corporate decisions is also referred to as resource investment strategy (Kuzgunkaya and ElMaraghy, 2007). For heterogeneous manufacturing systems composed of flexible, reconfigurable and dedicated machines, an optimization model was introduced by Bruccoleri and Perrone (2006), minimizing the production costs by optimal investments in the different machine types. More approaches exist that apply search metaheuristics to identify the proper configuration of manufacturing systems with heterogeneous resources (Deif and ElMaraghy, 2007; Renna, 2016; Youssef and ElMaraghy, 2007), while Renna (2010) proposed an agent-based solution to manage capacity exchange among production lines combining different resource types. When discussing the production planning and control levels of changeable systems, five important enablers have to be considered: *modularity, scalability, neutrality, adjustability* and *compatibility*. In-line with the physical changeability enablers of assembly systems as described in Section 2.3, throughout the thesis, the first two features are emphasized, as the analyzed systems are composed of modules providing the scalability of the system as a whole (Wiendahl et al., 2007). When discussing reconfigurable assembly systems, the modularity and scalability are hand-in-hand, as the entire system can be scaled up or down by increasing or decreasing the number of modules (Putnik et al., 2013). To identify the best capacity scaling policies of reconfigurable systems, system dynamics (Deif and ElMaraghy, 2006; Elmasry et al., 2014), dynamic optimization (Lanza and Peters, 2012), and also genetic algorithm based methods have been proposed (Abbasi and Houshmand, 2011; Wang and Koren, 2012).

Although various methods exist to manage production systems composed of different resource types, rule-based approaches frequently used in practice, without considering the continuous adjustment of capacities when deciding about the system configurations, and assigning products to the different resource types (Ceryan and Koren, 2009). The reason for this relies in the specialty of production environment operating with rapid reconfigurations, while the above introduced methods regard mostly long term reconfigurations of manufacturing systems. The rule-based approaches applied in industrial practice rely on corporate knowledge in production costs and possible future scenarios, and split up the product portfolio to low and high runner product groups, assigning them to reconfigurable/flexible and dedicated resources respectively (to be discussed in detail in Section 3.5).

A more important lack of state-of-the-art system configuration methods relies in the approximation of future expected costs, regarding especially the cost factors related to the operation of certain configurations with reconfigurable resources. Within strategic system configuration, firms need to make decisions about investments in different resources, considering long term market forecasts, as well as the actual system configuration. While these planning decisions mostly affect the physical architecture of the system, medium term planning is responsible for adjusting the production to the already existing capacities. Although some solutions exist that consider tactical planning aspects in the early design and configuration phase of the systems (Hu et al., 2011; Koren and Shpitalni, 2010), these methods got little scientific and research attention so far. The throughput and major performance indicators of systems in the design phase are mostly estimated base on the bottleneck operations (Li et al., 2014), without respecting the expected production sequences and the resulting setups and changeovers that can highly affect the system's performance (Battini et al., 2011; Boysen et al., 2007; Nazarian et al., 2010). More specifically, the production planning and the related operational costs are not considered by practical and theoretical production management approaches, often resulting in wrong investment decisions (Gyulai et al., 2014a). These facts are valid especially for assembly systems with dynamically changing structures, resulted by the reconfigurations. These systems require special production planning models that are capable of managing the short-term reconfigurations, usually applying a common pool of modules shared by the assembly lines. Concluding the above thoughts, an important objective of the presented research is bridging gap between strategic and tactical level decisions by providing system configuration methods that are capable of considering the future expected operation costs based on the tactical level production plans.

2.5 Robust production planning and scheduling

Besides the system configuration problem of modular assembly systems solved in the coming sections of the thesis, the second main contribution relies in a novel, robust production planning method that aims at tackling the uncertainties resulted by the *human factor* as a side-effect of the allocated flexible manpower in manually operated assembly systems.

2.5.1 Robustness in production

Regarding special planning requirements needed by the modular structure of the analyzed systems, from capacity management perspective, an important characteristic of manual and hybrid assembly systems is their scalable capacity through the assigned human resources. It means that a given assembly system can be operated by different headcount of human operators, resulting in the adjustability of the system's output rate. Therefore, human capacity requirements always need to be in balance with the system configuration and the applied production plan in order to reach the expected production rate. The production planning layer of the supply chain planning matrix is responsible for transforming customer orders into production orders by solving lot-sizing problems that match the order stream with available capacities, resulting in a production plan (Meyr et al., 2015). Production plans that rely on deterministic parameters often fail to cope with the dynamic effects of the execution environment and the considerable uncertainty of the underlying planning information, and their outcomes typically strongly rely on a single input data scenario (Kouvelis and Yu, 2013). In order to prevent the losses caused by the optimistic planning with idealistic parameters, robust techniques are mostly desired. *Robustness* in production planning involves refined approaches that aim at handling predictable or unpredictable changes and disturbances. They respond to the occurrence of random events with *reactive approaches* (Monostori et al., 2007; Pfeiffer et al., 2007), or protect the performance of plans by anticipating to a certain degree the occurrence of uncertain events with *proactive approaches* (Herroelen and Leus, 2004; Tolio et al., 2011).

Both fields of *robust optimization* and *robust production* are emerging, thus different definitions of robustness exist in theory and applied in practice (Kouvelis and Yu, 2013). However, according to Stricker and Lanza (2014), there is a common idea of robustness, which builds the basis for most of the existing definitions: *robustness describes the stability against different varying conditions.* Focusing on production, the robustness shall stabilize the systems' performance in case of varying conditions, and in case an unexpected event occurs, robustness has a positive effect on the system's performance. Seeking for a more specific definition of robustness, one can distinguish four main categories in the literature. In the first, strictest case —adopted from sensitivity analysis in operations research—, (i) a solution (e.g. the optimal solution) is called robust if it remains unchanged, even despite the change of considered influencing factors (Koltai and Tatay, 2011). In the second case (ii), a solution is called robust if it remains close to optima besides any variation of the regarded influencing factors. In the third case (iii), the solution is considered to be robust in case it is feasible under the considered variation of influencing factors, and its deviation from a target is small enough (Dellino et al., 2012). In the fourth case (iv), the solution is robust if it is feasible, and its selected measures stay within the predefined thresholds (Beyer and Sendhoff, 2007). Throughout the thesis, the third (iii) definition of robustness is considered, and a solution is called more robust than another one in case the deviation of its key measure is smaller than that of the other solution.

2.5.2 Calculation and evaluation of robust production plans

Efficient ways of taking uncertainties into account, and to achieve more robust solutions are either applying *stochastic models* (Naeem et al., 2013; Sahinidis, 2004) (e.g., by estimating the underlying stochastic processes), or using *adaptive and cooperative approaches*, which allow prompt responses to changes and disturbances (Monostori et al., 2010). A promising approach in reactive scheduling is the application of *multi-agent systems* that provide robust, error-prone plans by implementing the collaboration among local-acting agents to achieve a global target (Zhang, 2017). Further approaches for managing uncertainties in planning rely on *minimax* optimization models that first appeared in game theory, and aim at minimizing a worst case scenario's maximal possible loss, e.g. the extra costs (Liu and Papageorgiou, 2013) or excess inventories (Boukas et al., 1995; Dong et al., 2011).

As deterministic models usually fail to provide executable plans due to the existence of uncertain and stochastic parameters (e.g. reject/scrap rates or manual processing times), *simulation-based optimization* (also referred to as simulation optimization) methods are often applied to calculate robust plans (Kouvelis et al., 2000). In general, they consist of a mathematical optimization model, in which the objective function or constraint(s) are represented by functions that are approximated by utilizing the results of simulation runs (Azadivar, 1999). The reason for applying simulation in these cases are the computational complexity or the lack of analytical form of the objective function and/or constraints. In production planning, simulation-based optimization is mostly applied by iteratively adjusting parameter values according to the results of simulation experiments, until the target values of the performance indicators are reached (Byrne and Hossain, 2005; Gansterer et al., 2014; Irdem et al., 2010; Laroque et al., 2012; Melouk et al., 2013).

Another promising approach towards the robust production planning is the *robust optimization*, which is a relatively novel field of operations research. While stochastic optimization techniques dating back at least to the '50s, the first interior-point algorithms for solving robust optimization problems were published in the late '90s by Ben-Tal and Nemirovski (1998). Robust optimization as a modeling technique is currently applied in various fields where robust solutions for a problem with uncertain parameters is requested (Bertsimas et al., 2011; Gabrel et al., 2014). According to Ben-Tal et al. (2009), the strength of robust optimization relies in its simplicity: if one assumes that the basic deterministic model of a problem already formulated, its robust counterpart can be defined easily by representing the selected parameters with uncertainty sets. In contrast to stochastic optimization methods, in robust optimization, we do not solve the problem utilizing the distribution functions and probabilities, but a solution is to be obtained that is feasible in any of the possible scenarios, even in the worst case (Gorissen et al., 2015). As a result, the calculated robust solution satisfies all the constraints that might be uncertain, and stays feasible in any of the situations represented by the optimization models.

A robust solution is always more "costly" than its deterministic counterpart, and the difference between the objective function values is called the cost of robustness that can be measured by different indicators, depending on the problem instance. In practice, various key performance indicators (KPI) can be applied to characterize the robustness of a production plan (Aytug et al., 2005; Naeem et al., 2013), however, total backlog (or the related service level) and lateness are used in most of the cases (Stevenson et al., 2005). Lödding (2012) defines backlog as the difference of the planned and actual outputs of the production, whereas lateness is a time-dimension metric measuring the difference between the actual and planned completion of production orders. Lateness is an execution related KPI, which is basically caused by the disturbances if the plan is not robust enough, accordingly, it characterizes robustness more efficiently as it strongly relies on the execution of the plan (while backlog is usually a variable of the planning model). The robustness of a plan often works against other efficiency criteria, hence, it means a trade-off is required if the objective is to increase robustness. The *cost of robustness* can have different forms, a simple example might be the cost of additional capacities that need to be allocated for the same amount of work (Kazemi Zanjani et al., 2010). In the relevant part of the thesis (Chapter 5), cost of robustness is measured with the difference of the total production costs that incur when executing a robust and non-robust plan.

2.5.3 Production planning in multi-stage systems

In the previous sections, the emphasis was put on the *vertical integration* of the planning approaches, more specifically on the link between the strategic level system configuration, and the lower level production and capacity planning methods. As assembly systems are mostly responsible for completing the final products, they are typically the last stage of the production process chains. Therefore, *horizontal integration* of the planning methods and the resulted plans are also important to harmonize the production of various production stages. Accordingly,*multi-stage planning* (often referred to as multi-level) approaches are needed to balance the production among the assembly lines and the preceding steps of the process chain. Considering deterministic, multi-level production planning models, several efficient approaches exist to solve even complex problem instances. The applied models are typically formulated as *multi-level capacitated lot-sizing problems (MLCLSP)*, aimed at minimizing the overall production costs involving setup and inventory costs. In most of the cases, so-called *echelon-stocks* are introduced in the model, representing the stock of components that are produced in different stages of the process chain (Pochet and Wolsey, 2006). In general, MLCLSP is formulated as a single optimization problem that determines the optimal amount of components to be produced in different time periods. Due to the highly complex nature of the problem, existing approaches are either seeking to implement efficient heuristics, or to *decompose* the problem and solve the resultant single level sub-problems sequentially.

As for the heuristics-based approaches, Sahling et al. (2009) proposed a new algorithm to solve the MLCLSP as a big bucket problem, allowing to produce any number of products within a period, however, partial sequencing of the orders is solved by determining the release of the first and last orders in each period. Helber and Sahling (2010) apply the same fix-and-optimize heuristics as it provides a flexible and most efficient known solution for the MLCLSP that can manage general product structures and consider the lead-times of products, nonetheless deviations and uncertainties of the parameters cannot be treated. Similarly, the aggregate production planning problem of a two-stage system is solved by Ramezanian et al. (2012), applying a genetic algorithm and tabu search. In contrast to heuristics-based approaches, decomposition-based solutions apply echelon-stock variables, simplifying the original multi-level problem to a series of single-item lot-sizing subproblems (Pochet and Wolsey, 2006). They require to run multiple planning models to solve the multi-level problem, however, these single stage models take significantly less computational efforts to be solved.

2.5.4 Towards robust, multi-level planning in practice

Although both multi-stage and robust planning have extensive literature, only a few solutions exist to solve the combined problem of them. Aghezzaf et al. (2011) propose an inventory-decomposition-based approach to solve the robust, multi level planning problem. Alem and Morabito (2012) apply robust optimization to solve a multi-stage planning problem from a furniture industry, whereas Schemeleva et al. (2012) propose a memetic algorithm to solve a similar problem. Kozłowski et al. (2014) introduce a predictive approach for multi-stage systems with stochastic parameters, however, this solution is more suitable for long-term planning with large order quantities. Kazemi Zanjani et al. (2010) apply an inventory-based decomposition for production planning in a manufacturing environment with random yield. The approach results in robust solutions, yet it considers aggregate and constant capacities, which is not suitable in case of assembly processes with stochastic processing times and flexible capacities.

The efficiency of the above approaches are proven, however, from practical point of view, most lot-sizing approaches are not suitable for everyday use due to the 'hard-wired' procedural heuristics that follow highly specific problem logics (Helber and Sahling, 2010). Production planning of multi-stage systems is a major step of material requirement planning (MRP) systems, most of which ignore capacity constraints and disregard setup, production, and inventory costs when deciding about lot sizes (Berretta et al., 2005). Without applying special MRP techniques to cope with finite resource capacities —e.g. the approach proposed by Na et al. (2008)—, the calculations can lead to capacity infeasible plans in industrial practice. Albeit enterprise resource planning (ERP) systems are significantly improved in the integration of material and capacity planning (Hvolby and Steger-Jensen, 2010), they are still often unable to perform satisfactory in a dynamic, uncertain environment (Tenhiälä and Helkiö, 2015). To tackle these challenges more efficiently, advanced planning and scheduling systems (APS) combine production planning and scheduling, and utilize ERP data to adjust the plans to the actual status of the production system (Fleischmann et al., 2005). Most APS software apply what-if analysis to determine the quality of the plan before releasing it to the shop-floor, and this analysis is often performed by simulation considering the latest shop-floor data (Ko et al., 2013; Krenczyk and Jagodzinski, 2015). These approaches enable to evaluate the production schedules in a proactive way, and to adjust them to the actual status of the physical system. Even though these methods offer efficient solutions to calculate feasible production plans, they do not consider the dynamics of the systems, nor the variability and uncertainty of the parameters that might have impact on the entire system's performance, but only use higher level planning data such as cycle times or expected lead times. Besides, APS systems are mostly applied for disturbance handling in a reactive way, as they support quick re-scheduling with rule-based scheduling algorithms (Barnett et al., 2004; Pinedo, 2012).

2.6 Modeling techniques in operations management

In operations management, various tools, techniques and technologies are applied to support decisions. In real practice, these decisions mainly correspond to the field of industrial engineering, which is an interdisciplinary branch of engineering science, conclusively, the most common applied tools also cover multiple fields, and encompass engineering, computer science and mathematics knowledge. The following sections introduce the basics of different models and computational tools that are mostly applied throughout the thesis.

2.6.1 Discrete-event simulation

One of the most widespread digital enterprise tools is *discrete-event simulation (DES)*, which is a computational instrument to analyze dynamic processes, even if stochastic parameters and uncertain events are to be considered. Similarly to the other tools discussed in Sections 2.6.2 and

2.6.3, simulation modeling is aimed at supporting decisions qualitatively or quantitatively by building a model of a real system, and making experiments with this model (Bangsow, 2010; Law and Kelton, 2000). Compared to the optimization models discussed in Section 2.6.2, the greatest benefit of using DES models is their advanced capability of representing even the underlying processes, without loosing the accuracy of results, or increasing significantly the computational time. Another main distinctness of simulation models are their nature of supporting decisions: whereas in optimization one expects to obtain the "best-among-all" solution for a certain problem (satisfying the constraints), simulation cannot provide such a result, but it is rather capable of predicting the outcome of various scenarios, meaning that the "best" solution can be selected only from the analyzed scenarios, and not from all possible/feasible ones.

In accordance with its name, DES works with a discretized time horizon composed of unequal time periods (Fishman, 2013). Those time periods are derived from the occurrence time of the events arise in the process under study. In a generic simulation modeling project, one implements the model by using predefined building blocks of the system, and then describes the logic of material and information flow among the elements of the system. When running an experiment with the model, a clock is started in the background, simulating the execution of events stored in self-organizing list by changing the state of the system affected by the event, adding the new events to the list and advancing in time with the clock (Page and Kreutzer, 2005). This modeling procedure enables to use relatively low computational efforts even in case of analyzing complex processes, and makes it possible to select the level of detail of interest by building either detailed or draft models.

Simulation models are built to support various decisions, accordingly, different kinds of experiments are defined to answer certain questions. Most often, simulation models are built in order to analyze existing systems' behavior under different production scenarios, to predict the performance change when an existing system is changed (physically or logically), or to estimate the performance of a planned system that not yet exists. Thanks to the advanced statistics engine of DES tools, detailed results can be obtained about the simulation experiments. In general, industrial engineers expect from simulation modeling to support the increase of systems' performance (e.g. utilization or output), decrease the losses (e.g. inventories) or to give them insight to the details of complex processes, understanding better their behavior. In practice, optimization is often combined with simulation to evaluate solutions under different scenarios, or even to support finding the optimal solution, achieved with simulation-based optimization methods (Law and McComas, 2000). Throughout the thesis, DES is mostly used to predict the outcomes of various production scenarios, which typically means the execution of different plans (pre-calculated e.g. with an optimization model) in a given production environment.

2.6.2 Mathematical modeling and optimization

Descriptive and *optimization models* are often created to describe the behavior of real production systems by using the language and concepts of mathematics (Will M. Bertrand and Fransoo, 2002). While descriptive models are mostly applied to analyze the systems behavior and performance applying the techniques and tools of queuing theory (Adan and Resing, 2002; Buzacott and Shanthikumar, 1993), optimization models are typically created in order to obtain the possible best solution for a certain problem; e.g. to calculate a production plan that satisfies the pre-defined constraints, while its execution results in the minimal costs (Lang, 2010). Such optimization models might have various forms and solution techniques, depending on the nature of relations that are applied to define the problem. In most cases, one is aimed at representing the problem with *constraints* and *objectives* that are linear functions of the *variables.* In several cases, this can be achieved only by simplifying some elements of the model, decomposing the problem, or linearizing the relations applying piecewise functions. However, these transformations often worth the efforts, as linear optimization problems can be solved efficiently considering the running time of the algorithms and complexity of the problem. Linear optimization problems – often referred to as programming models – have the following canonical form defined by (2.1).

$$\begin{array}{lrcl} \text{maximize} & & \mathbf{c}^{\intercal}\mathbf{x} & \\ \text{subject to} & \mathbf{A}\mathbf{x} & \leq & \mathbf{b} \\ & \mathbf{x} & \geq & 0 \end{array} \tag{2.1}$$

The first term of the model is called the objective function that one wish to minimize or maximize. The objective function is the linear function of the decision variables denoted by vector $\mathbf{x}$, similarly to the constraints that are represented by the second term of the model. The problem is solved by calculating the values of the decision variables, while respecting the constraints that bound the possible values of $\mathbf{x}$.

From modeling perspective, important bound on decision variables is their integrity, expressing their possible set of values. Such constraints mostly express that decision variables are binary $x \in \{0, 1\}$, or integer $x \in \mathbb{Z}$ that often characteristic to production planning models, if assignment decisions are made (e.g. producing a product in a certain period or not), or capacities are among the decision variable (e.g. number of machines is integer). Optimization models with integer and real decision variables are called *mixed-integer programming (MIP)* models. From computational viewpoint, such integrity restrictions significantly increase the problems' complexity, as they cannot be solved by the polynomial time simplex algorithm, but search algorithms – e.g. the branch and bound — need to be applied (Winston and Goldberg, 2004). In the following parts of the thesis, production planning problems are mostly formulated as MIP models in a declarative way, applying mathematical modeling software tools, which provides both the environment, as well as the set of solver algorithms (Heipcke, 1999).

From managerial perspective —as mentioned earlier in Section 2.5.1— solving an optimization problem does not necessarily mean that the obtained solution is the one that should be strictly followed or directly applied, but it is recommended to perform a *sensitivity analysis* beforehand. By doing so, one can get answers for questions about the robustness of a solution, the influence of constraints on the structure of the solution and also on the value of the objective function (Jansen et al., 1997). Koltai and Terlaky (2000) present the three main types of sensitivity considered by the decision makers when changing either the coefficients of the objective function, or the elements of vector $\mathbf{b}$ on the right hand side in (2.1). The latter implements the calculation of shadow prices that provide information about the change of the objective function value, realized when performing a unit change in the right hand side elements (Bertsimas and Tsitsiklis, 1997). In production management, typical example is the analysis of profit growth/costs savings when increasing the available capacities by a single item.

2.6.3 Statistical learning

In the era of cyber-physical system, a vast and ever increasing amount of data is available about the production processes. This data is applied directly in many different ways to support decisions, however, there are lot more opportunities for further application if data is used in an indirect way by identifying its usability to obtain underlying information with the use of various analytical tools. *Statistical learning* in general means "learning from data": if historical or quasi-real time measurements and data samples are available, one often wish to use learning methods to build models upon the available set of data, and use these models to predict the outcomes of different future scenarios (Friedman et al., 2001).

Based on the nature of available data samples, *supervised* and *unsupervised* learning are distinguished; if both a set of input variables and outputs (affected by the input variables) are available among the samples, we use supervised learning tools to identify the correlation among the variables. Accordingly, supervised learning is used to build models that are capable of predicting the values of new output variables, based on the corresponding input variables. In case of categorical output values, the task is called *classification*, whereas in case of numerical output, it is called *regression*. Based on the applied algorithm and learning technique, various types of regression models exist, of which the most common ones are *linear models, tree-based models* and *support-vector regression*. As for the linear regression, the goal is to fit a model on the data to predict the numerical output value Y, by knowing input variables $x_1 \dots x_n$. Multiple (more than one input variable) linear models take the following form (James et al., 2013):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon. \tag{2.2}$$

When fitting a model, the values of parameters $\beta_0 \dots \beta_n$ are calculated, which are called regression *coefficients*, among those β_0 is the *intercept term*. By nature, the model fitting procedure always incurs some *error*, denoted by ε that needs to be minimized. Important to highlight that although linear models might seem to be overly simple, they often outperform more sophisticated methods (Friedman et al., 2001; Marden, 2013). This can be achieved by careful selection of input variables (often referred to as features), or – similarly to the optimization modeling – linearizing the non-linear correlation, e.g. with piecewise linear functions. Important to highlight that efficient solution for statistical learning tasks always require *domain specific knowledge*, in order to ask the right questions, collect the appropriate data and select/define the best features in the best model elements applying feature engineering techniques. In further parts of the thesis, regression models are fitted in order to combine them with linear programming models. Therefore, linear models are primarily analyzed: in case of nonlinear correlations are to be tackled, new features are introduced, or linearization is applied. In this way, – as detailed in the following chapters – event the complex correlations from the analyzed ones can be captured accurately by applying linear functions.

Chapter 3

Capacity management of modular assembly systems

In Chapter 3, a novel, hierarchical framework for modular assembly systems is presented that is capable of providing capacity management solutions on each level of the classical planning hierarchy. On the highest level, system configuration and product-assembly system assignment decisions are taken on a longer horizon, supported by the predicted results of tactical level decisions. On the latter level, the integrated capacity and production planning is performed to minimize the costs on a medium term, putting special emphasis on modular reconfigurable systems built up of lightweight resources. Then, the short-term task scheduling problem of these systems is solved to minimize the overall human efforts on the operational level (Figure 3.1). The chapter is structured as it follows. First, the description of the production environment is provided in Section 3.1, highlighting the operation related costs of the considered modular system. Next, the capacity management problem is specified, focusing on each level considered in the hierarchy. In Section 3.3, a simplified version of the complete capacity management problem —called line assignment— is described and solved on a product basis. The solution of this problem is applied as a proof-of-the-concept to extend the approach for solving the more complex system configuration problem on a product portfolio basis with the hierarchical framework as detailed in Section 3.4. The applicability of the proposed framework is justified by the results of a real industrial case study from the automotive sector.

3.1 Description of the production environment

In order to specify the capacity management problem in question, the main structural and operational characteristics of the considered modular assembly system are discussed first. For the visualization of the system's general characteristics, charts (Figure 3.2-3.4) of numerical analysis are provided that related to a case study introduced in Section 3.5.

3.1.1 Structure and operation of modular assembly systems

In the capacity management of modular assembly systems, the production environment consists of a heterogeneous resource set, including assembly modules that are either dedicated, flexible or reconfigurable ones. The modules are only capable to be used for assembly purposes, therefore, machining and other technologies/resources are not part of the system under study. Modularity

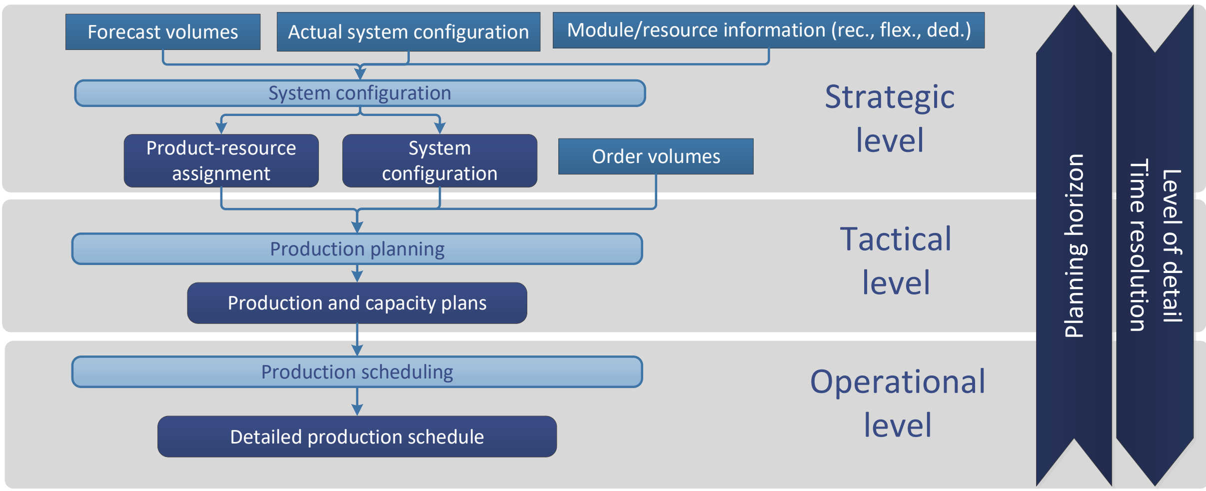


Figure 3.1. Illustration of the planning problems on different levels of the hierarchy, addressed by the proposed capacity management framework.

of the system (ElMaraghy and Wiendahl, 2009; Wiendahl et al., 2007), as a whole, manifests in the modularity of lines that constitute the system; as the lines are built up of modules from the same (dedicated, flexible or reconfigurable) type, as discussed in Section 2.3. The dedicated and flexible modules are commonly used in industrial practice, however, reconfigurable ones are cutting-edge of assembly technology, thus they got special emphasis in the following capacity management methods. In order to provide a comprehensive method, the different resource types and assembly lines are put under the concept of modular systems, providing an "umbrella", under which different resource types are managed within a common framework.

Important characteristic of the considered problem is the modularization of assembly processes, more specifically that operations are assigned to standardized modules enabling to assemble a product either in a dedicated, reconfigurable or in a flexible assembly system. Besides the assignment, product families are formulated to determine the set of products that can be assembled together on flexible resources. In practice, modularization step is done manually, as it requires complex engineering knowledge about product and processes. First step of the procedure is the overview of existing resources, as well as the analysis of products and processes. In the worst case, products and the corresponding assembly resources are overly diverse, thus investment in modularization will not return. Otherwise, patterns in the processes and similarities among the applied resources can be identified, allowing to define the set of required modules.

In the analyzed case, system configuration regards only the set of assembly resources, and relies on the modularization of the assembly system. Most assembly operations are done manually by operators, however, some of the modules can be automated for extra costs. The modules are configured sequentially according to the successive assembly operations required by the assembled product. The required number of modules and also the corresponding processing times are known, however, the number of operators can be changed periodically, and the length of a period is typically a working shift. The structure and operation of the dedicated and flexible lines are rather simple: the modules are installed on the shop-floor, and capable of producing a certain product (dedicated line) or a family of products (flexible line). These modules can be equipped with automated devices, decreasing the operator requirements, and/or increasing the production rate. The dedicated lines do not require changeovers, while the flexible modules have definite, sequence independent setup times to switch from one product variant to another (Gyulai et al., 2014a).

Reconfigurable lines are composed of modules that are standard, mobile workstations, applied to perform a single assembly operation type (e.g. screwing or pressing). Each module is equipped with adjustable resources, and standardized interfaces for the fixtures as well as for the pneumatic, voltage, and data connectors. The operation (reconfiguration cycle) of the reconfigurable system is the following:

- Configuration: First, the assembly line is built-up by means of the standard modules (which are required by the actual product), by moving them next to each other according to the assembly process steps.
- Setup: The operators perform the necessary setup tasks, e.g., plug in the pneumatic connectors, and place the required fixtures on the modules. Then, operators prepare the parts that need to be assembled.
- Assembly: The operators assemble the products according to the predefined batch size.
- Deconfiguration: After a batch is completed, the operators dismantle the lines, and move back the excess modules (which are not required by the following product type), to the resource pool.

Applying the above procedure, different assembly lines can be built on the shop floor from a common resource pool.

3.1.2 Costs of production with different resource types

The following section introduces the main factors, influencing the investment and operation costs of different system and resource types. In order to compare the system types and illustrate their characteristics that important from capacity management perspective, Figures 3.2-3.4 are provided, based on the numerical results of a case study detailed in Section 3.5. Each point of these scatterplots corresponds to the evaluation of a given production scenario, representing a system configuration and an applied production plan.

Costs of system configuration applying heterogeneous resource pool

The general driver of capacity management is the need for staying competitive in a dynamic environment by keeping the production costs at the lowest possible level, while providing the desired production rate. In the analyzed problem, the objective is to minimize the total production costs, characterizing the operation of the assembly system during a certain period. When discussing system configuration and product-assembly system assignment, usually longer periods are considered as these decisions raise operation-, as well as investment-related questions. Therefore, the objective function of the system configuration model is the sum of various cost factors that are rather diverse when applying different resource types to perform the same tasks. Figure 3.2 depicts the total costs realized in relation to three different system types, within a numerical study and each point of the chart corresponds to a given configuration. Although the correlations between total costs and capacity requirements show somewhat linear trends, very high deviations can be observed in case of the different configurations, mostly resulted by the dynamic behavior of the system structures, especially those of the reconfigurable and flexible systems'. This phenomena is further investigated and detailed by the following analysis of investment and volume costs.

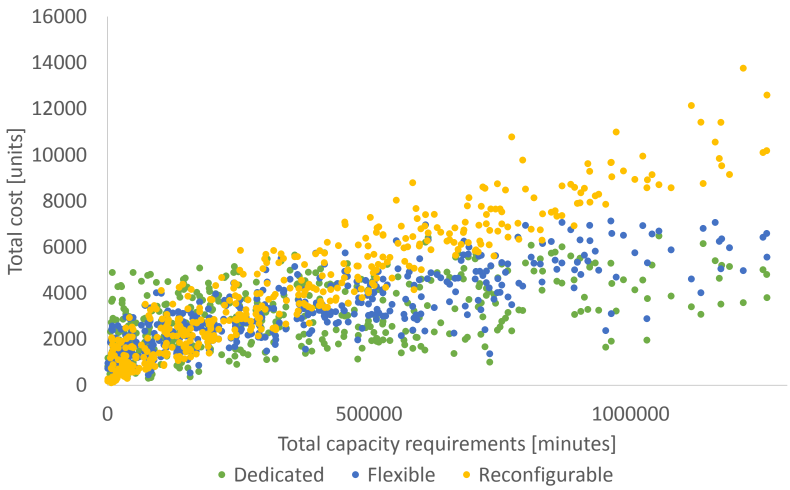


Figure 3.2. Comparison of the total costs in the three system types.

Investment costs mostly depend on the number of products exist in the portfolio, accordingly, if a new product is added to the portfolio, the necessary resources may need to be purchased. Analyzing the number of products and the related investment costs, it is seems that costs correspond to dedicated resources are higher than those of the other two, in case a certain number of assigned products is exceeded. It is resulted by the product-specific resources that should be purchased for each product, moreover, dedicated systems often have a higher degree of automation that also increases the purchase cost of the resources. On the contrary, flexible and reconfigurable resources can be shared among more different products, which means that the investment costs are in a nonlinear correlation with the number of the assigned product types.

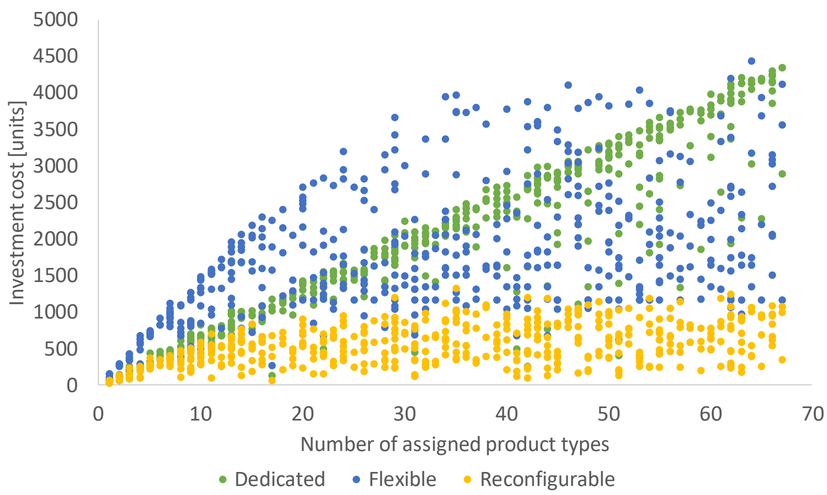


Figure 3.3. Comparison of investment costs in the three system types.

This assumption is justified by the results of a numerical study in Figure 3.3, illustrating that linear correlation between the number of assigned products and the investment costs is valid only for the dedicated systems with static structure. In contrast, when applying reconfigurable and flexible system configurations (points of the chart) with dynamic structures, the amount of necessary resources, and therefore, the investments costs are in nonlinear correlation with the number of products.

Besides the investments, operation of production systems also entails significant costs. These operation costs mostly depend on the volume of the products that are assembled in a certain period. In the analyzed case, operation costs are composed of the followings: cost of setups, assembly operators (salaries) and latenesses. As products have different processing times, not the assembled volumes but rather the net, total capacity requirements should be analyzed when discussing the production rate related, changing volume costs. This total capacity requirement is the sum of manual operation times multiplied by the volume of products to be assembled. Comparing the three system types, one can identify that assembling products in high volumes with dedicated resources is cheaper than with reconfigurable or flexible ones (Figure 3.4). The reason for this relies in the higher throughput of the lines, resulting in shorter makespan than e.g. producing the same volumes in a reconfigurable system. In addition, dedicated systems with automated resources require less human workforce than flexible and reconfigurable ones.

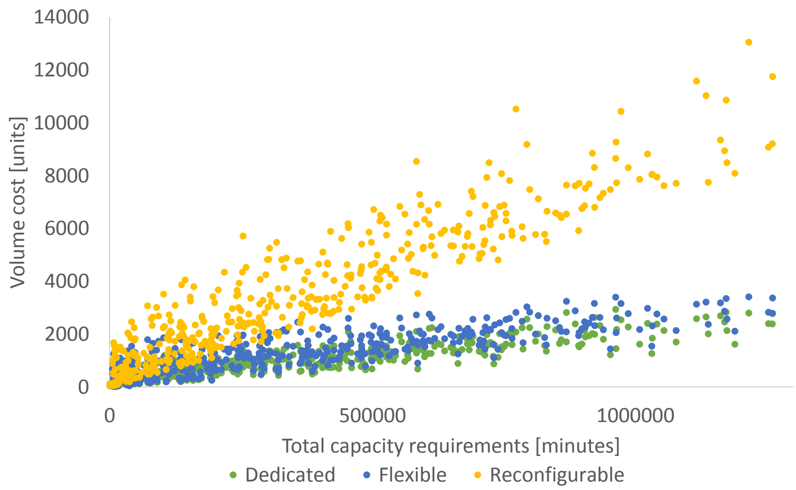


Figure 3.4. Comparison of the volume-dependent costs in the three system types.

As a conclusion of the cost analysis, there is no rule of thumb to assign a singular product to one of the three resource types, but the correlations among a set of products' assembly processes and resource usage need to be addressed to find the right balance among the amount of dedicated, flexible and reconfigurable resources. This can be achieved by formulating the system configuration problem in a multi-period optimization model, allowing for the time-to-time reassignment of the product to different resource types.

This periodic product-assembly system assignment and the related system configuration decisions entail that the resource pool is continuously adapted to the system architecture. Therefore, not only investment costs need to be considered, but there is often an opportunity for selling the unnecessary resources, e.g. when a product is switched from a dedicated to a reconfigurable system. In these cases, the book value of assets can be calculated by decreasing its previous period value with the depreciation rate over the useful lifetime of the asset (the residual value of asset is also considered in the end of its lifecycle), and it can be interpreted as a price, for which a resource can be sold (if this option exists) at a certain point of time.

Costs of line assignment with outsourcing option

Besides the internal costs realized when operating modular assembly systems with heterogeneous resources, some firms have the option of outsourcing production to external suppliers. Outsourcing is financially advantageous in two main cases: either if there is not enough internal capacity to serve the demands in peak periods, or in the second case, when production of the end-of-lifecycle products would decrease the internal efficiency under a critical level (e.g. low utilization and high space requirements). In these cases, the product specification and the corresponding technological description —and also the equipment in some of the cases— are provided to the suppliers, in order to produce the requested parts and products in the contractual volume defined by the OEM. As the outsourcing option does not raise system configuration decisions, a problem with a simplified cost model can be specified, which is similar to the one in the system configuration, however, it should be capable of handling the external capacities (outsourcing) applying a simplified model for the internal capacity management. This problem is called *line assignment*, and it is aimed at defining the cost-optimal product-assembly system assignment, considering that dedicated and reconfigurable assembly resources are available as internal capacities, moreover, the company an option of outsourcing the production to external suppliers. In contrast to the comprehensive system configuration problem and the related cost model defined in Section 3.1.2, the line assignment problem is not aimed at precisely defining the set of resources necessary for production, nor it is capable of capturing the costs resulted by the underlying correlation factors when different products are assigned to the same resource types. The line assignment problem is aimed at subdividing the set of products into subsets assembled on the dedicated and reconfigurable lines, and also products to be outsourced. In case of dedicated resources and outsourcing, the production costs can be assigned directly to individual products. As introduced earlier, the use of product-specific dedicated lines is characterized with relatively high fix costs, and low volume costs (Figure 3.2). Analogously, for an outsourced product, the total product-dependent cost is composed of a small fix cost and a relatively high volume cost. In contrast, the costs related to the reconfigurable lines depend on the actual product mix and the production plan adopted, and cannot be directly divided among individual products. Therefore, the overall production cost incurred in the reconfigurable system is aimed at capturing by a function incorporating the investment costs and the volume costs. A key challenge in the line assignment problem is computing, as well as predicting this cost for an arbitrarily selected subset of products assigned to the reconfigurable system.

3.2 Description of capacity management related problems

Having the boundaries of the analyzed modular system defined, the formal definitions of the capacity management problem and the related sub-problems in question are provided in Section 3.2.

3.2.1 Specification of the system configuration problem

Objective and decisions related to system configuration

The objective of capacity management is to match the capacity of the modular assembly system with the needs related to the continuously changing product portfolio. Besides, time-varying order stream also needs to be respected when deciding about the applied resources. These aspects lead to a complex system configuration problem, namely to determine the set of applied assembly resources, and assign the products to these resource sets (Figure 3.5). In the configuration problem, three different system types $s \in S$ are considered: reconfigurable ($s = r$), flexible ($s = f$) and dedicated ($s = d$) systems. The main objective is to minimize the total cost incurs on a certain time horizon U. This cost is the sum of investments in different production resources Λ_u^{s}, as well as the production rate related expenses Γ^{s}, characterizing the operation of system s. Additional costs χ of assigning the products to a new system type, and depreciation of the resources Ψ are also considered.

These costs can be minimized by making right decisions in each time period $u \in U$, assigning the products to one of the three system types. These actions are naturally accompanied by system configuration decisions, adjusting the production capacities to the customer order stream. In each planning period $u \in U$, all products $p \in P$ need to be assigned to one system type $s \in S$. Besides, the investment costs with the amount of additional modules n_j from each type $j \in J$ also need to be determined (Figure 3.5). These investment and system configuration decisions are taken on a strategic level, considering volume forecasts f_{pu} and a relatively long time horizon (typically some years). Additional complexity in the problem is introduced by the order volumes that change over time, and related forecasts are uncertain.

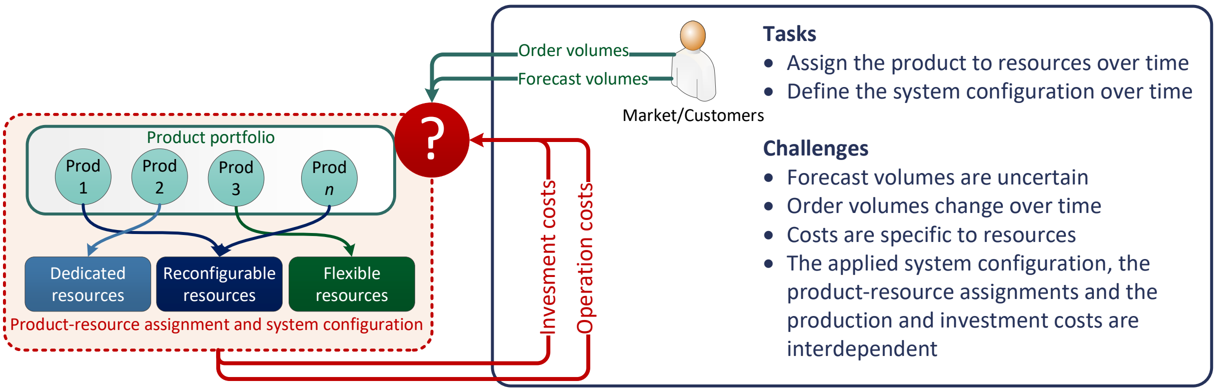


Figure 3.5. Illustration of the analyzed product-assembly system assignment and system configuration problem, highlighting the special tasks and challenges.

Constraints

Although it would be simple to assign each product to dedicated resources that will certainly provide the target production rate, this strategy would lead to excess costs due to the facts summarized in Section 3.1.2. When configuring the system, various constraints need to be considered, e.g. the available shop-floor space $m^{\max}$ and the available human workforce $h^{\max}$ as technological constraints. Besides, different cost factors are considered: the purchase cost of the modules m_s^{price}, the cost of setups c^{set} and reconfigurations c^{rec}, the salaries of the operators c^{opr} and the operation costs c^{opn} of the modules. In the considered problem, modules of different system types s can have different level of automation m_s^{aut}, influencing the total time required to assemble a certain product in a selected system type. The space requirement m_s^{space}, and also the purchase cost m_s^{price} of modules depend on the system type. Concluding the above thoughts, the system configuration problem is solved by utilizing the advantages offered by the combination of the different resource types, and assigning the products to proper resources according to multiple criteria. Applying an optimization model, the cost-optimal system configuration —capable of providing the desired production rate— is to be obtained in each decision period.

3.2.2 Production planning problem in modular assembly systems

In case of the dedicated resources, calculation of the investment costs is quite straightforward, as the amount of modules to be purchased is given for each product. As highlighted earlier, flexible and reconfigurable systems are characterized with dynamic operation, which means that resources are shared among different products, therefore, the required number of modules is not only product-, but also operation-dependent. Conclusively, the performance of modular reconfigurable assembly systems and incurring costs are strongly influenced by the system configuration, and also by the applied planning and scheduling policy (Gyulai et al., 2014b, 2012). As introduced in Section 3.1.2, volume-related operational costs in these dynamic systems are also rather complex to estimate, as they can be operated economically if several product types (family) are assigned.

It is also essential that strategic decisions influence the execution of tactical-level production plans, hence the link between these levels is of crucial importance. The assembly system configuration together with the product-assembly system assignments and the available capacities constrain decisions when planning the production, therefore, planning aspects need to be considered when configuring system. Production planning decisions in the analyzed capacity management problem are responsible for calculating the production lot sizes, with the objective of minimizing the total production costs on a medium-term, discrete time horizon. In the considered production planning problem, the objective is to determine the lot sizes x_{nt} by matching the available internal capacities (human and machine) with the customer demands. The planning horizon T is divided into time buckets $t \in T$ with equal length t^{w}, and a given set of orders $n \in N$ corresponding to products $p \in P$ need to be completed. To perform the assembly operations, $j \in J$ different module types are available, and each type is dedicated to a single operation type. The amount of modules from each type j is limited by the resource pool r_j^{avail}.

Based on the above assumptions, the production planning problem is specified as it follows. The production lot executions are to be determined with the binary decision variables x_{nt}, specifying if order n is executed in period t. Each order n is associated with a product type p specified by p_n, the order volume q_n and a due date t_n^{d}. The parameters c_n^{h} and c_n^{l} respectively express that both early and late execution of the orders are penalized with extra costs, according to the following formula:

$$c_{nt} = \begin{cases} c_n^{\mathrm{h}} q_n (t_n^{\mathrm{d}} - t) & \text{if } t < t_n^{\mathrm{d}}, \\ c_n^{\mathrm{l}} q_n (t - t_n^{\mathrm{d}}) & \text{otherwise.} \end{cases} \tag{3.1}$$

The products are characterized with their total manual processing time t_p^{proc}, setup time t_p^{set} and the number of modules r_{jp} required by type j. The objective of planning is to minimize the overall costs realized over the horizon, including the following factors: operator c^{opr}, setup c^{set}, deviation c_{nt} and operation c^{opn} costs. The essence of assembly technology is that human resources can be flexibly adjusted to change the throughput of the lines. Therefore, production planning is performed together with capacity planning by calculating the allocated headcount of operators in each period.

3.2.3 Task scheduling problem in modular assembly systems

On the lowest, operational level of the production planning hierarchy, the task scheduling problem related to modular assembly systems is introduced as it follows. By definition, scheduling corresponds to the execution of individual production orders, therefore, its time horizon is shorter than that of the production planning. The scheduling horizon is a single planning time bucket $t \in T$ with the length of t^{w}, thus an individual scheduling problem instance can be defined for each time period of production planning. The main input parameters of scheduling are the lot sizes production orders and the corresponding operator headcounts (both are decision variables of the planning model), specifying the assembly tasks and the assigned human capacities. The objective of production scheduling is to minimize the total headcount of operators h^{total} working in period t, by calculating the execution start t_n^{start} (and end t_n^{end}) times corresponding to a task n assembled in t. A proper schedule means that the task execution times are distributed over the period enabling operators to switch between the lines they are working at, when an executed task is finished. The applied resolution of the scheduling horizon is much higher (e.g. minutes) than that of the planning, as the horizon length and problem size allow it. One can distinguish human and machine resources in the scheduling problem, constraining the solution in a different way. As for the machines, a modular line and the assigned assembly modules —determined by the planning model— are capable of processing a single task n at any point of time (disjunctive resource constraint). Besides, as many operators need to be assigned to each task that is specified by the solution of production planning model.

3.3 Product-based line assignment

As a simplified version of the problem specified in Section 3.2, the line assignment problem (Section 3.3.1) is solved first on product basis, in order to analyze the efficiency of the approximation models that predict the costs characterizing the operation of modular reconfigurable assembly systems. In this case, a typical problem related to the management of end-of-lifecycle products is analyzed: whether it is economically worth to assemble a product in a reconfigurable system, in a dedicated system or outsource it to a supplier. As stated earlier, the main challenge in this case is the correct approximation of costs relating to the reconfigurable lines, in order to obtain the optimal product-assembly system assignment. The method is aimed at tackling this challenge by applying regression and decision models defined on a single product basis, taking a step towards the solution of general capacity management problem, where more detailed system configuration and flexible resources are also considered, and correlations among the products' processes are captured.

3.3.1 Specification of the product-based line assignment problem

In an assembly system that consists of dedicated and reconfigurable resources, the key decision within capacity management is allocating each product to a dedicated or a reconfigurable line or, alternatively, outsourcing it to a supplier, while minimizing the total production cost. Since in the reconfigurable system the production costs depend on the product mix in question and the production plan adopted, line assignment and production planning of the reconfigurable system are strongly related (Gyulai et al., 2012). Therefore, the product-based method focuses on solving the line assignment and capacity planning problems (Figure 3.6).

When searching for the optimal allocation, current customer orders and also forecast volumes are considered on a predefined time horizon U. The total production cost φ_u^{s} with a resource type $s \in S$ in a period $u \in U$ is composed of the investment Λ_u^{s} and volume costs γ_u^{s}. The total cost characterizing the operation of dedicated and reconfigurable lines over the planning horizon U in the line assignment problem is calculated with (3.2).

$$\Phi^{\mathrm{s}} = \sum_{u \in U} \varphi_u^{\mathrm{s}} = \sum_{u \in U} \left(\gamma_u^{\mathrm{s}} + \Lambda_u^{\mathrm{s}}\right) \qquad \forall\ s \in \{r, d\}\,. \tag{3.2}$$

In the line assignment problem, the following assumptions are made. The reconfiguration cost c^{rec} are an order of magnitude smaller than the above cost components, and order volumes are assumed to be available on the planning horizon, based on the forecast volumes f_{pu}. All products can be assembled either with a reconfigurable or with a dedicated line. It is assumed that the capacity of a single line is sufficient to assemble the product in the desired volume, and therefore, the option of dividing the order volume between different production modes can be ignored. Moreover, machine prices m_s^{price} and the costs of human operators c^{opr} are constant over time. The length of planning time horizon U is a few months, with re-planning periods $u \in U$ on a rolling horizon basis. While line assignment is a continuous-time decision that can be revised only during periodic re-planning, production planning is performed on a discrete time scale with time units $t \in T$ corresponding to one period.

3.3.2 The proposed decision workflow

As highlighted earlier, the key of solving the line assignment problem relies in the proper approximation of the overall costs Φ^{r} characterizing the reconfigurable resources $s = r$. Therefore, a hierarchical workflow is proposed for solving the integrated line assignment and production planning of the reconfigurable system (Figure 3.6). Integration is established via feedback from production planning to line assignment, in the form of multivariate linear regression for estimating the cost function Φ^{r}. Both line assignment and production planning are iterated over time in a rolling horizon framework, which results in a potential time-to-time relocation of the products among lines as order and forecast volumes vary. In each step of periodic re-planning, investment costs are calculated to reflect the necessary changes in the resource pool with respect to the current capacities.

The objective of line assignment is to decide whether a certain product $p \in P$ should be assembled with a dedicated ($s = d$) or with a reconfigurable line ($s = r$), or it should be outsourced ($s = o$) (Figure 3.6). While the production costs Φ^{s} in the dedicated system and by outsourcing can be computed as a closed form of the input parameters, the costs of reconfigurable system Φ^{r} depend on the actual product mix. Therefore, this cost is predicted by using multivariate linear regression model (see Section 2.6.3), fitted on the production costs resulted by randomly generated scenarios. For the regression, the following calculation model is applied:

$$\varphi_u^r = \beta_0 + \beta_1 \sum_{p \in P} z_{pu}^r + \beta_2 \sum_{p \in P} f_{pu} t_p^{\mathrm{proc}} z_{pu}^r + \sum_{j \in J} \left(\beta_j \sum_{p \in P} r_{jp} z_{pu}^r \right) + \varepsilon, \tag{3.3}$$

where the βs are unknown parameters that are estimated, β_0 is the intercept and ε is the error term. By neglecting ε, the formula above can be rearranged as follows:

$$\begin{aligned} \varphi_u^r &\approx \beta_0 + \sum_{p\in P}\left(\beta_1 z_{pu}^r + \beta_2 z_{pu}^r f_{pu} t_p^{\text{proc}} + \sum_{j\in J}\beta_j z_{pu}^r r_{jp}\right) \\ &= \beta_0 + \sum_{p\in P} z_{pu}^r \underbrace{\left(\beta_1 + \beta_2 f_{pu} t_p^{\text{proc}} + \sum_{j\in J}\beta_j r_{jp}\right)}_{\alpha_{pu}} = \beta_0 + \sum_{p\in P} z_{pu}^r \alpha_{pu}. \end{aligned} \tag{3.4}$$

Conclusively, it is enough to estimate only the product-dependent α_p values subsequently. The regression was computed on randomly generated production scenarios in the reconfigurable assembly system, solved by the production planning model presented in Section 3.2. The scenarios were randomly split into independent training and test sets. As regression assigns a separate production cost α_p to each product p, line assignment can be performed for individual products, by comparing the production costs associated to the three candidate production modes. Products p where α_p is the lowest among the costs will be produced on reconfigurable lines, and hence, constitute the subset of products assigned to reconfigurable resources in u. Therefore, the solution of product-based line assignment problem can be obtained by calculating the production costs for each resource type and in each period $u \in U$. The production planning model solved in period $u \in U$ —as formulated below— calculates the plan applying this given product subset (for which $z_{pu}^r = 1$) as determined by solving the line assignment problem. Besides the products assigned to the reconfigurable system, the forecast volumes f_{pu} are also correspond to a planning period $u \in U$.

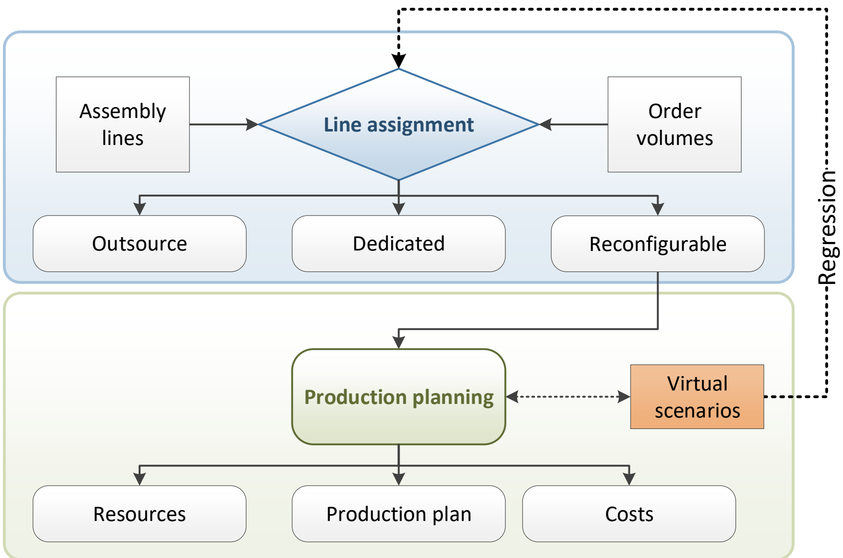


Figure 3.6. Workflow of the product-based capacity management of modular assembly systems: the line assignment problem is solved by applying regression models on virtual scenarios, to predict the product-dependent α_p values (Equation 3.4).

In the proposed workflow— illustrated by Figure 3.6—, the lower level is responsible for solving a production planning problem, related to the reconfigurable system, and addresses the integrated configuration optimization and resource assignment of the system. Planning is solved on a discrete time horizon T with time units $t \in T$ corresponding to individual periods. The planning problem is formulated as a mixed integer linear program as follows:

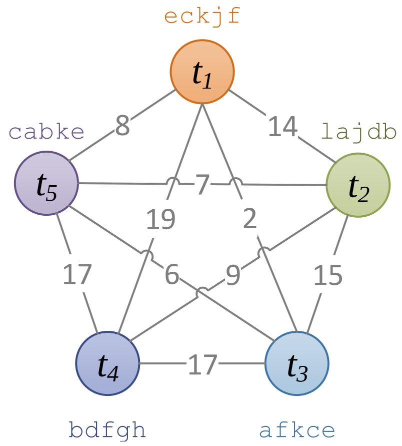
$$\text{minimize}$$
$$\sum_{j=J} m_r^{\text{price}} c_j^{\text{m}} n_j + c^{\text{opr}} \sum_{t\in T}\sum_{p\in P} y_{pt} + \sum_{t\in T}\sum_{p\in P}\sum_{j\in J} c^{\text{opn}} r_{jp} y_{pt} \tag{3.5}$$
$$\text{subject to}$$
$$n_j + r_j^{\text{avail}} \geq \sum_{p\in P} r_{jp} y_{pt} \qquad \forall\, j \in J,\ t \in T \tag{3.6}$$
$$\left\lceil \frac{f_{pu} t_p^{\text{proc}}}{t^{\text{w}}} \right\rceil = \sum_{t\in T} y_{pt} \qquad \forall\, p \in P \tag{3.7}$$
$$n_j \geq 0, \quad y_{pt} \in \mathbb{N}^0 \qquad \forall\, j \in J,\ t \in T,\ p \in P. \tag{3.8}$$

The objective (3.5) is to minimize a cost function, composed of the purchase price of the machines that are not readily available in the current resource pool, the personnel costs, and the operation costs. Constraint (3.6) specifies the required number of modules ($n_j + r_j^{\text{avail}}$) from each type in each period t, while equality (3.7) states production rate needs to achieve the target volume (sum of order volumes). Constraints (3.8) define the variable domains. The resulting production plan specifies the setups y_{pt} that implicitly express the number of lines assembling product p in period t, and the amount of modules n_j to be purchased in each period. This version of the model is applied for solving the production planning problem based on virtual scenarios. In this case, the option of investing in new modules n_j is possible, if the forecast volumes f_{pu} for the upcoming period u justify it. In case the production planning model is applied on real scenarios, the set of available modules are applied as a constraint, without the option of investment. In these cases, the planning model is applied with the modifications of replacing (3.5) with (3.9), and changing constraint (3.6) to (3.10).

$$c^{\text{opr}} \sum_{t\in T}\sum_{p\in P} y_{pt} + \sum_{t\in T}\sum_{p\in P}\sum_{j\in J} c^{\text{opn}} r_{jp} y_{pt} \tag{3.9}$$
$$r_j^{\text{avail}} \geq \sum_{p\in P} r_{jp} y_{pt} \qquad \forall\, j \in J,\ t \in T \tag{3.10}$$

The above models ignore the cost and time of reconfiguration, and lead to a plan in which the sequence of the periods can be changed arbitrarily. This is enabled by the quick reconfigurability of the system that can be done within the period in which a certain product type is produced. In the line assignment problem, typically, low-volume end-of-lifecyle and aftermarket products are assigned to the reconfigurable system (and some of them are outsourced). Due to the low volumes and larger due date time windows, the time requirement of the batches are rounded to a planning period (3.7), enabling to perform the reconfigurations. These factors lead to a model that matches the reconfigurable resources with the production, however, changeovers are not optimized.

In order to minimize the number of reconfigurations, a sequencing problem is solved that re-orders the periods, but leaves the system configuration unchanged within each period. This can be represented as a Traveling Salesman Problem (TSP), in which vertices are the periods, while the cost of an edge is the number modules to be changed between the consecutive configurations (Hoffman et al., 2013). In each period, more reconfigurable lines are operated in parallel, however,



	a	b	c	d	e	f	g	h	i	j
a	0	3	1	4	3	2	3	4	2	2
b	3	0	3	7	5	6	4	3	4	3
c	1	3	0	5	6	5	6	3	4	5
d	4	7	5	0	2	3	4	3	4	6
e	3	5	6	2	0	4	4	5	6	2
f	2	6	5	3	4	0	3	2	2	3
g	3	4	6	4	4	3	0	4	5	6
h	4	3	3	3	5	2	4	0	3	4
i	2	4	4	4	6	2	5	3	0	4
j	2	3	5	6	2	3	6	4	4	0

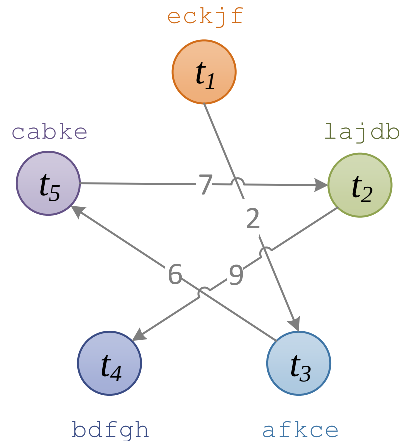


Figure 3.7. Sequencing problem with $|T| = 5$ periods, formulated as a TSP: the representation of the problem as a symmetric TSP with complete graph (left), the applied symmetric distance matrix (middle) and the optimal production sequence (right), obtained by solving the TSP. The letters encode different product types, of which five was assembled in each period (e.g. products `e, c, k, j` and `f` are assembled in t_1). The costs of the edges are the number of modules to be changed: e.g. the cost of edge $\{t_1, 1_3\}$ is $c_{t_1,t_3} = 2$, as only one line is changed from producing `j` in t_1 to `a` in t_1, and the number of modules to be changed according to the distance matrix is 2.

none of them are configured to assemble the same product type. In order to calculate the costs of the edges, a string distance function was applied to calculate the number of different modules between any pair of products. The products are encoded by strings, and the applied characters identify the various module types requested by the product type. It is assumed that changeovers are sequence independent that lead to a symmetric TSP instance, and the sequence of the periods can be arbitrarily changed, thus the problem is represented by a complete graph (Figure 3.7). Calculating a production plan and the corresponding distance matrix, the solution of the resulted TSP leads to a new production plan that satisfies the original constraints (feasible), while it minimizes the number of reconfigurations.

3.3.3 Experimental results

The proposed product-based capacity management method was tested on an industry-related dataset, considering historical order and forecast volumes, and real assembly lines. The product portfolio consists of $|P| = 67$ products with diverse volumes and assembly processes. The training dataset for the regression contained 80 random-generated production planning problem instances, with distinct order volumes, and the production planning problem was solved for each of these instances, providing the production costs as a result.

The multivariate regression was computed using the R environment, applying its general linear regression function, which took ca. 2 seconds (R Core Team, 2016). According to (3.4), the input variables of the regression model were the total work contents, the number of products assigned to the system, and the total number of required modules from each type, while the output is the corresponding operational cost. This provided an appropriately precise prediction of the production cost for the reconfigurable system, with a value of $R^2 = 0.987$, as shown in Figure 3.8 (a ”perfect” fit would be represented by the diagonal line connecting the equal values of actual and predicted costs). The line assignment problem was solved iteratively using a rolling

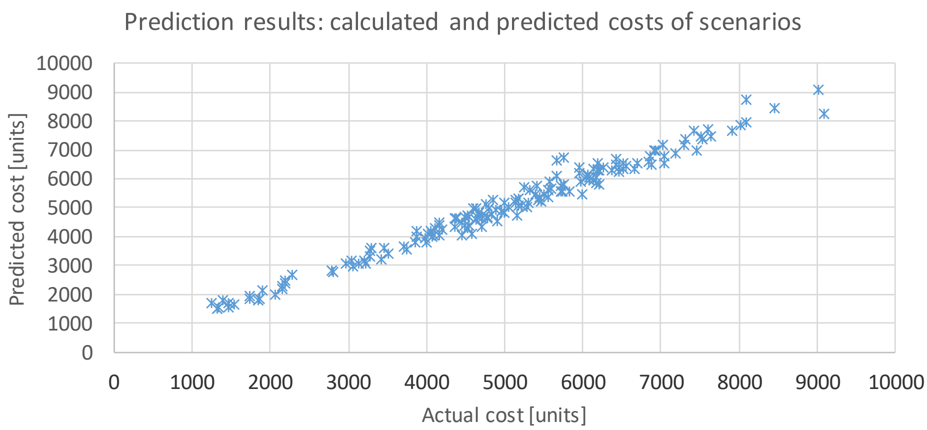


Figure 3.8. Comparison of the production costs predicted by multivariate linear regression and calculated by production planning; each point of the scatterplot corresponds to a scenario (orders).

horizon scheme, with a fix horizon of three months in each iteration. In order to evaluate the efficiency of the method, a reference solution was considered in which all products were assigned to dedicated lines. The results show that applying reconfigurable lines, the proposed method makes significant cost savings possible, even in case of fluctuating order streams. It is typical that savings are higher (up to 30%) in periods with lower production volumes, whereas they are lower (10-15%) around peak production volumes (Figure 3.9).

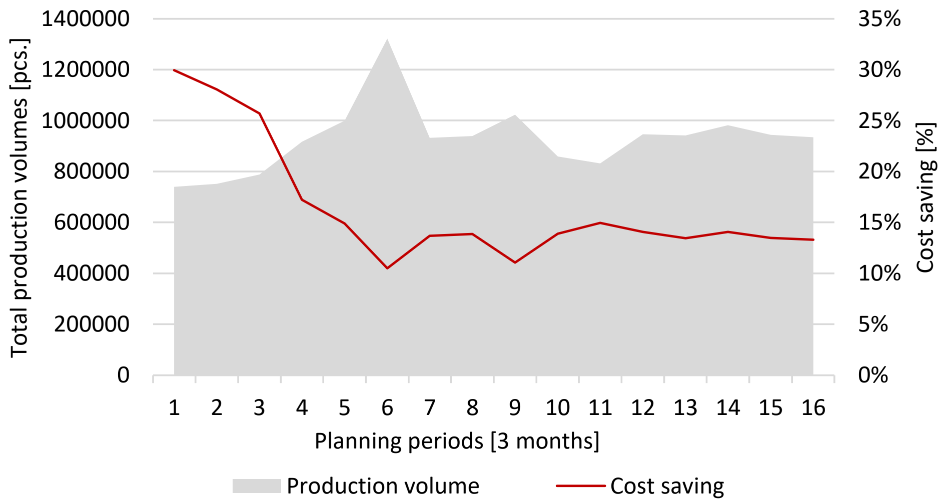


Figure 3.9. Results of line assignment: cost savings and production volume over a four-years horizon.

Since most products in the industrial dataset were in the end stage of their lifecycle or produced to aftermarket, their production volumes typically decreased over the considered four-years horizon. Accordingly, the number of products assembled in the dedicated system slightly decreased, whereas the number of products in the reconfigurable system and products outsourced increased over time (Figure 3.10). The production planning model was run on the set of products assigned to the reconfigurable system, the proposed MIP model was solved using *FICO® Xpress* and its default branch and bound method (FICO, 2017). In the test problem instance, a three-

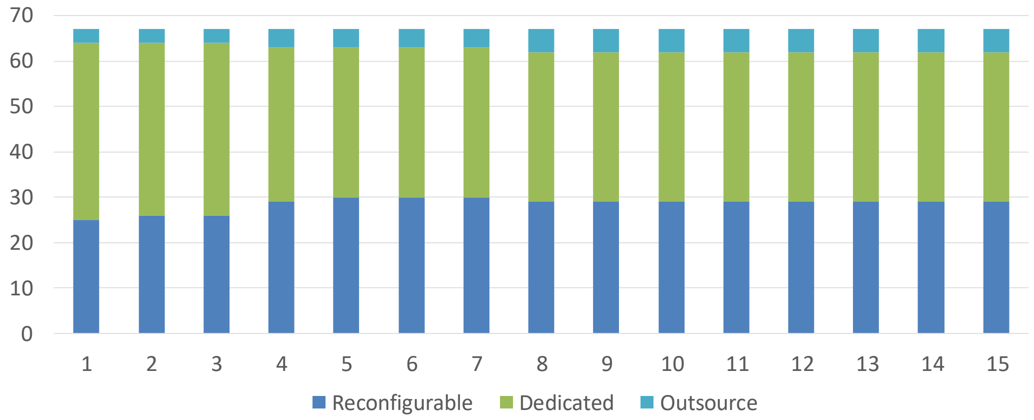


Figure 3.10. Results of line assignment: number of products assembled using the three production modes over a four-years horizon.

months horizon was considered, composed a number of $|T| = 270$ working shifts. The search was run until an optimality gap of at most 4% was achieved, which required 116 seconds on average. The subsequent sequencing problem was solved using the open-source solver *LKH* (Helsgaun, 2000), which implements the heuristic of Lin and Kernighan (1973). Solving the problem using the default randomized restart strategy with 10 runs required 59 seconds altogether (TSP with $n = 270$ cities). The sequencing reduced the number of reconfigurations by 51%, resulting in a significantly smoother production plan, as depicted by Figure 3.11.

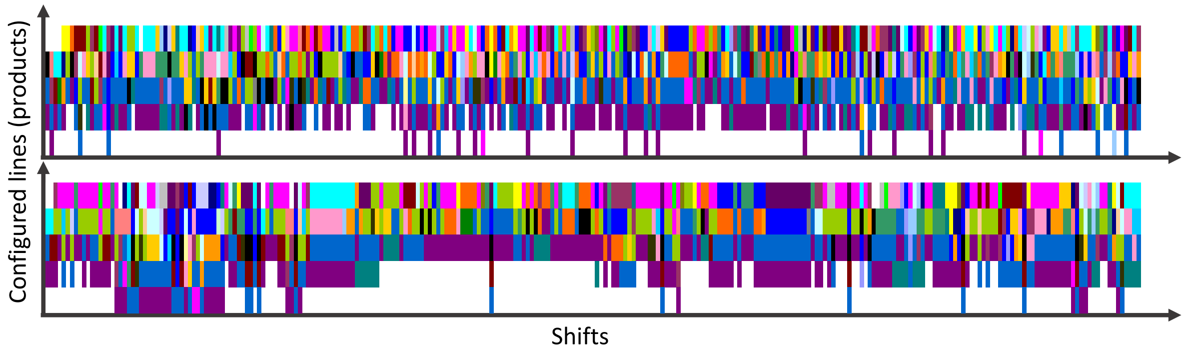


Figure 3.11. A sample production plan before (above) and after (below) performing the sequencing: each product is identified by a unique color, and white color represents empty configuration.

3.3.4 Approximation of costs with nonlinear models

In the presented case study, linear regression model for the approximation of costs (related to the reconfigurable system) provided satisfactory results, as the correlation among the selected variables was strong enough, although the system structure was dynamically changing. The greatest benefit of applying such a linear model is the option of integrating it in a linear optimization model, as it can be considered as a constraint when solving the line assignment problem. It was assumed in the problem specification (Section 3.3.1) that costs of reconfigurations c^{rec} are an order of magnitude smaller than other cost parameters. This assumption is valid for modular assembly systems, in which the modules enable fast reconfigurations. In case the system structure is dynamic, moreover, the reconfiguration costs are also high, linear regression models might not provide accurate predictions of the future costs, e.g. in case of modular systems with heavy technological modules in which slower reconfigurations require additional efforts (e.g. human and/or machine requirements).

In order to solve the product-based line assignment problem in such cases, more sophisticated regression models might be necessary. James et al. (2013) argue that tree-based statistical learning models should be used in cases, when nonlinear and complex relationship among the variables are observed. Therefore, tree-based regression (and classification) models, called *random forests* were applied by Gyulai et al. (2014b) to predict the costs Φ^{s}. Random forests build decision trees over bootstrapped samples of the training data, applying only a subset of predictors in each step. These uncorrelated trees are then averaged by bootstrap aggregation, resulting in reliable and less varying trees in the final model (Breiman, 2001). The most important drawback of this (and all tree-based models) method is that regression cannot be applied beyond the ranges of the training dataset.

Random forests can be applied to predict the costs related to the reconfigurable system on a product basis, however, representative training dataset needs to be created either by solving the production planning model, or performing a comprehensive simulation analysis. In the latter case, optimal production plan cannot be applied, however, several various plans can be analyzed quickly to determine the resulting costs (Gyulai et al., 2014b). In this way, a candidate training dataset can be generated, and random forests can be applied to predict the future costs. Similarly to the method presented in Section 3.3.2, a product should be assigned to system $s \in S$ of which the predicted costs is the lowest. With this approach, more complex cost functions can be approximated by capturing the possible nonlinear correlation among the several variables.

3.3.5 Discussion about the product-based decisions

In Section 3.3, the line assignment problem of modular reconfigurable assembly systems was solved on a product basis. Within this problem, the task is to assign the product portfolio to dedicated or reconfigurable resources, or to outsource production to a supplier in a way that the overall costs are to be minimized. The main challenge is the approximation of the costs characterizing the operation of the reconfigurable system, as they strongly depend on the adopted product mix, as well as on the applied production planing policy. This challenge is mainly introduced by the correlation among the assembly steps and the corresponding modules —taken from a common resource pool— that characterize the assembly processes of products assigned to the reconfigurable system.

In order to tackle these challenges and obtain a result that takes into consideration the future production costs, a novel approach was presented facilitating the economical production of a diverse, varying product portfolio consisting of high- and low- volume products. The approach offers an integrated way for the assignment of products to dedicated or reconfigurable resources and for the production planning of the reconfigurable ones. An essential element of the method is the prediction of costs with multivariate linear regression, supporting the solution of line assignment problem. The training dataset of regression was provided by solving the lower level production planning problem on a set of virtual scenarios to represent the possible behavior of the system and obtain the resulting costs. The line assignment problem could be solved by selecting the lowest among the product-dependent α_p parameters, describing the cost of producing product p in the reconfigurable system. This cost can be compared to the outsourcing or dedicated production cost of product p, and the lowest among them is selected in each period $u \in U$ to assign product p to system s cost-optimally.

Although this product-based assignment works properly for cases, for which the assumptions of the problem are valid, there might be more complex problem instances asking for more sophisticated models. Therefore, the product-based line assignment method is considered as a proof-of-the-concept that production costs of dynamic system structures and operation modes can be predicted efficiently with regression models built over virtual scenarios. The basis of this concept is that a lower level production planning problem needs to be solved multiple times to generate production scenario–cost data samples for a statistical model building. In case linear models can be fitted on the data, the cost models can be applied directly in linear optimization models as constraints or objectives (Gyulai, 2014a,b). This concept will be utilized in the following sections introducing a hierarchical capacity management framework, enabling to solve complex system configuration problem in a similar way, and capable of handling flexible assembly resources, as well as nonlinear correlation among the products' processes in optimization models.

3.4 Hierarchical capacity management framework

Extending the capabilities of the workflow proposed to solve the line assignment problem, a three-stage hierarchical capacity management framework is proposed. In contrast to line assignment, a system configuration problem (Section 3.2.1) is solved on the highest, strategic level incorporating the long-term managerial decisions related to the internal capacities. In the system configuration problem, dedicated, flexible and reconfigurable systems are all considered by planning their capacities and assigning the products to them, on a cost-basis. In order to solve this strategic-level problem, the tactical level production planning (Section 3.2.2) aspects also need to be respected to calculate the investment and operational costs that will certainly incur in the future, based on the forecast volumes. Relying on the results achieved in the product-based line assignment, the framework applies sophisticated models to deal with multiple decision criteria, diverse cost functions and complex relations among the strategic and tactical decisions (Section 3.2.1). The novelty of the framework stems from the strong link between the system configuration and production planning levels, applying regression models to approximate the investment and operation costs. The results are derived from the general concept applied in Section 3.3.2, namely the prediction of costs applying function approximation models on virtual scenarios. In contrast to the previous workflow, the proposed capacity management framework consists of three hierarchical stages as represented by Figure 3.12: the system configuration, production planning, and production scheduling levels. The latter is added to the framework as a new element, extending the capacity management method to all levels of the classical production planning hierarchy. On the lowest, operational level, the tactical level production plans are applied as input data of the operational level scheduling. The proposed scheduling model solves the problem defined in Section 3.2.3, calculating the sequences and execution times of the production lots on the short term, as well as the corresponding operator-task assignments, minimizing the total headcount of human operators within a given period.

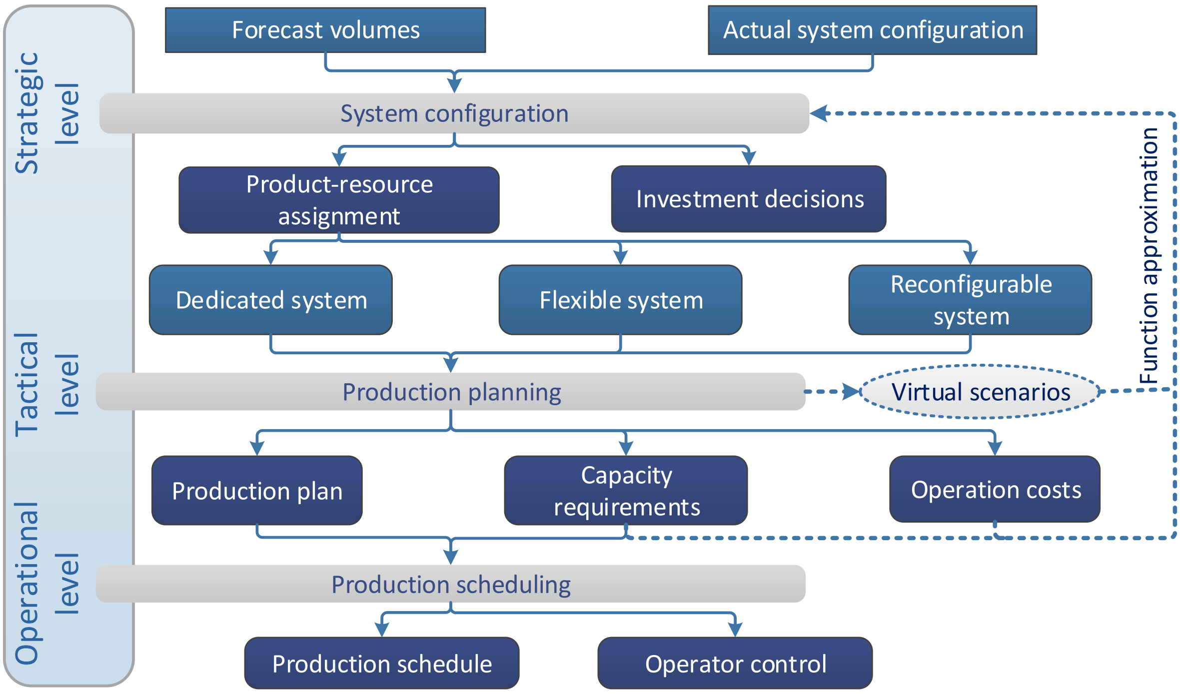


Figure 3.12. Capacity management framework for modular assembly systems.

3.4.1 Feedback link from tactical to strategic level

The strategic level of the framework aims at solving the system configuration problem and assigning the products to different system types, according the objectives and constraints defined in Section 3.2. As an applied system configuration with its available capacities represents strict constraints when planning the production, these strategic decisions need to consider tactical level aspects as well. Assigning a product to a system type implies that the assignment cannot be changed until the next period, therefore, decision makers are allowed to adjust only the release of orders when planning the production. As the operation of reconfigurable and flexible systems shows dynamic characteristics, calculation of the costs is not straightforward. Consequently, the idea behind the proposed capacity management framework is to implement the lower, tactical level production planning models, and apply a function approximation feedback from tactical to strategic level to predict the costs that are relevant on the latter.

Similarly to the product-based workflow, this can be achieved by solving the production planning model on several virtual scenarios for each resource type, representing possible real situations. In case the correlation among the input variables (order stream) and the related costs is strong enough, regression functions can be applied to predict the results of various scenarios without having detailed data about the order stream, typically available only on the tactical level. As discussed in Section 3.3.5, great advantage of the regression models is their integrability in optimization models: in case linear approximation functions can be defined to predict the selected parameters, the approximation functions can be directly applied in linear optimization models as objective functions or constraints.

Analyzing the system configuration problem, forecast volumes of each product are known a-priori, however, the necessary investments cannot be calculated without information about the costs that will characterize the system's operation. Resource sharing in flexible and reconfigurable assembly systems strongly influences the system's performance and thus the operational costs

(Section 3.1.2). Consequently, neglecting capacity constraints in the production planning model of the virtual scenarios and introducing the capacities as decision variables result in near to optimal, integrated capacity and production planning decision. In this way, the required operator headcount, number of modules, setups and reconfigurations can be calculated, and regression models can be defined upon them. These functions are then applied in the mathematical model of system configuration as constraints: having linear approximation functions, linearity of the existing optimization model can be kept.

3.4.2 Production planning of modular assembly systems

Regression models are defined over solutions of the production planning model, therefore, this part of the capacity management framework is described first.

Constraints and decisions in production planning

As previously stated, production planning in this method is responsible for calculating the production lot sizes applying a discrete time horizon T, with the resolution of a working period $t \in T$. Orders $n \in N$ are given for the planning horizon, and an order is characterized by its completion due date t_n^{d}, inventory holding c_n^{h} and lateness c_n^{l} cost, and the volume of ordered products q_n. As there are individual due dates for each order, both early delivery and lateness are penalized with a deviation cost c_{nt}, expressed by (3.1). The objective function of the production planning model minimizes the total costs that incur over the planning horizon and defined as the sum of deviation, setup, reconfiguration, operator and machine operation costs (3.11). Decision variables are the execution time (period) of the orders (x_{nt}), specifying if order n is assembled in period t or not. Calculation of the setups is possible by introducing the continuous indicator variable y_{pt} that gives if product p is assembled in period t. In this model, a virtual operator pool is defined, therefore, the number of operators is a decision variable, defined as a real type in order to boost the computation. Accordingly, production planning model of the characterized modular assembly system is defined as it follows:

minimize

$$\sum_{t\in T} c^{\mathrm{opr}} h_t + \sum_{p\in P}\sum_{t\in T} c^{\mathrm{set}} y_{pt} + \sum_{t\in T}\sum_{n\in N} c_{nt} x_{nt} + \sum_{t\in T}\sum_{n\in N}\sum_{j\in J} c^{\mathrm{opn}} r_{jp_n} x_{nt} \tag{3.11}$$

subject to

$$\sum_{t\in T} x_{nt} = 1 \qquad \forall\, n \in N \tag{3.12}$$

$$h_t \le \sum_{j\in J} n_j \qquad \forall\, t \in T \tag{3.13}$$

$$x_{nt} \le y_{pt} \qquad \forall\, t \in T,\ n \in N,\ p = p_n \tag{3.14}$$

$$\sum_{i\in N} x_{nt} q_n t_p^{\mathrm{proc}} m_s^{\mathrm{aut}} + y_{pt} t_p^{\mathrm{set}} \le h_t t^{\mathrm{w}} \qquad \forall\, t \in T,\ p = p_n \tag{3.15}$$

$$h_t \in \mathbb{Z}^+, \quad n_j \in \mathbb{Z}^+, \quad y_{pt} \in \{0,1\}, \quad x_{nt} \in \{0,1\} \qquad \forall\, j \in J,\ t \in T,\ n \in N,\ p = p_n \tag{3.16}$$

The first constraint states that each order should be assigned to exactly one time period t, therefore, order splitting is not allowed (3.12). Each module is operated by a single operator, thus the headcount of operators in each period is limited by the total number of the simultaneously applied modules (3.13). Constraints (3.14) and (3.15) define the number of setups in each period and the requested headcount of operators, respectively. Both setup time, and also the automation degree of different systems are considered. In case of the reconfigurable system, constraint (3.15) is modified with the additional time of reconfigurations that is $y_{pt}t_p^{\text{rec}} \quad \forall\, p \in P \ \mid \ p = p_n$.

Planning model of virtual and real scenarios

Additional system-specific constraints mostly specify the number of required modules, as resource sharing and operation mode depend on system type. The functionality of the production planning model is twofold: it can be either used to calculate real plans for definite order sets, or applying virtual scenarios, the regression models can be defined upon the results. These two operation modes are distinguished when specifying the following, system dependent constraints: in real planning situations the number of available resources is given, in contrast, the purpose of regression models is to estimate this value. Therefore, the number of modules n_j from each type $j \in J$ is applied as a constraint in the real planning case, whereas in the virtual case, it is part of the objective function.

Reconfigurable:

$$\sum_{p \in P} r_{jp} y_{pt} \leq n_j \qquad \forall\, j \in J,\ t \in T \tag{3.17}$$

Dedicated:

$$\sum_{p \in P} r_{jp} = n_j \qquad \forall\, j \in J \tag{3.18}$$

Flexible:

$$r_{jk}^{\text{f}} = \max_{p \in P}\{r_{jp} | k_p = k\} \qquad \forall\, j \in J,\ k \in K \tag{3.19}$$

$$\sum_{k \in K} \sum_{p \in P} r_{jk}^{\text{f}} y_{pt} \leq n_j \qquad \forall\, j \in J,\ t \in T \tag{3.20}$$

In case of the dedicated system, the calculation of necessary modules is straightforward: it equals to the total number of modules from each type required by the products assigned to dedicated resources (3.18). Dynamics of the reconfigurable system is different, only the assembly processes constrain the necessary number of modules (3.17). Operation of the flexible system is slightly similar to the reconfigurable case, however, assembly resources are shared among a limited set of products (clusters, K) only. Equation (3.19) specifies the number of modules for each cluster, in this model, it equals to the maximal number of modules for each type considering all products in the cluster. This representation guarantees that all products are assembled with the least possible modules, and the number of applied modules is greater than this value (3.20).

Having the values n_j defined for each system type, the production planning models can be separated for real and virtual scenarios. In real planning cases with definite number of resources (resource pool), constraints (3.17)-(3.20) are applied together with inequality $n_j \leq r_j^{\text{avail}} \quad \forall\, j \in J$, expressing that the number of applied modules for assembly must be less or equal to the number of available modules. In contrast, constraints (3.17)-(3.20) are also applied in the virtual scenarios, without limiting the number of resources (r_j^{avail} is neglected), however, the objective function in this case is added a new element to minimize the number of applied resources. The objective function, replacing (3.11) in the virtual scenarios is the following:

$$\text{minimize} \sum_{t\in T} c^{\text{opr}} h_t + \sum_{p\in P}\sum_{t\in T} c^{\text{set}} y_{pt} + \sum_{t\in T}\sum_{n\in N} c_{nt} x_{nt} + \sum_{t\in T}\sum_{n\in N}\sum_{j\in J} c^{\text{opn}} r_{jp_n} x_{nt} + \sum_{j\in J} c_j^{\text{m}} m_s^{\text{price}} n_j \tag{3.21}$$

The last element of the function defines the purchase cost of resources that wish to be minimized, consequently, capacities and production are planned together in the virtual cases.

3.4.3 Strategic system configuration

Decision variables and constraints of the system configuration model

Decision variables z_{pu}^s specify the system $s \in S$, to which products $p \in P$ are assigned over time $u \in U$. Important to identify that the length, and thus the notation of time periods differ from the ones applied in the production planning model, as strategic decisions in the system configuration model consider longer periods $u \in U$. The formulated system configuration model —solving the problem stated in Section 3.2— is the following:

$$\text{minimize}$$

$$\sum_{s\in S} \Gamma^{\text{s}} + \sum_{s\in S}\sum_{u\in U} \Lambda_u^{\text{s}} + \underbrace{c^{\text{dep}} \sum_{s\in S}\sum_{u\in U}\sum_{p\in P}\sum_{j\in J} z_{pu}^s r_{jp} m_s^{\text{price}} c_j^{\text{m}}}_{\Psi} + \underbrace{c^{\text{chg}} \sum_{s\in S}\sum_{u\in U}\sum_{p\in P}\sum_{j\in J} w_{pu}^s n_j}_{\Theta} \tag{3.22}$$

subject to

$$\sum_{s\in S} z_{pu}^s = 1 \qquad \forall\, p \in P,\ u \in U \tag{3.23}$$

$$\sum_{j\in J}\sum_{p\in P}\sum_{s\in S} z_{pu}^s r_{jp} m_s^{\text{space}} \le m^{\max} \qquad \forall\, u \in U \tag{3.24}$$

$$\sum_{s\in S} \left(\beta_{s0}^{\text{op}} + \beta_{s1}^{\text{op}} \sum_{p\in P} z_{pu}^s f_{pu} t_p^{\text{proc}} \right) \le h^{\max} \qquad \forall\, u \in U \tag{3.25}$$

$$w_{pu}^s \ge z_{pu}^s - z_{p,u-1}^s \qquad \forall\, p \in P \tag{3.26}$$

$$\Lambda_u^{\text{d}} \ge \sum_{j\in J}\sum_{p\in P} w_{pu}^{\text{d}} n_j c_j^{\text{m}} m_d^{\text{price}} \qquad \forall\, u \in U \tag{3.27}$$

$$\Lambda_u^{\text{s}} \ge \lambda_u^s - \lambda_{u-1}^s \qquad \forall\, u \in U, s \in \{r, f\} \tag{3.28}$$

$$g_{bu}^s \ge z_{pu}^s \qquad \forall\, s \in S, u \in U, b \in B = \{1 \dots p_b\} \tag{3.29}$$

$$z_{pu}^s,\ w_{pu}^s,\ g_{bu}^s \in \{0,1\}, \quad \Lambda_u^{\text{s}} \ge 0 \qquad \forall\, p \in P, s \in S, u \in U, b \in B = \{1 \dots p_b\} \tag{3.30}$$

The objective function (3.22) is the total cost resulted by the assignment of products to different resource types. The function has four main elements, namely the cost Ψ of using resources (analogous to the depreciation of the resources, if linear formula is applied), the cost Θ of change (when switching the assignment of a product from a resource type to another), the cost Λ_u^{s} of investments and the volume costs Γ^{s}. Equation (3.23) states that a product must be assigned to one of the three system types in any period $u \in U$. The next inequalities represent the limited shop-floor space (3.24) and the maximal number of operators per period (3.25). In case of human operators, the required workforce in a certain period is approximated by a linear regression model, applying the total work contents of product types as input variables.

Elements of the objective function

Having the operation characterized by the previous constraints, further parts of the model specify the objective function elements. Some costs are approximated, thus —in order to keep the linearity of the optimization model—, multinomial linear regression models are applied. As the volume costs Γ^{s} cannot be expressed explicitly, they are approximated by regression models in a form of $\Gamma^{\mathrm{s}}\left(z^s_{pu}, g^s_{bu}\right)$ as detailed in (3.44). As introduced earlier, the calculation of investment costs in the dedicated system $\left(\Lambda^d\right)$ is straightforward if the set of assigned products is given: the number of modules required by each product are summed and multiplied with the purchase cost of the modules (3.27). In the case of reconfigurable and flexible resources, investment costs are calculated in two steps: first, the value λ^s_u of assets realized at a certain period u is approximated with regression models in a form of $\lambda^{\mathrm{s}}_u(z^s_{pu})$ for resource types $s \in \{r, f\}$ as detailed in (3.45). Having these values approximated, the second step is the calculation of investments realized when taking a decision in the beginning of period u. As the values of shared resources in the flexible and reconfigurable systems are additive by nature, the investment costs Λ^s_u that are realized as a result of a decision taken in u equals to the difference $\left(\lambda^{\mathrm{s}}_u - \lambda^{\mathrm{s}}_{u-1}\right)$ in the values of assets (3.28) in two consecutive periods. The cost of change Θ incurs when the assignment of a product is switched as a result of a strategic decision, and additional efforts in design and installation are required. Besides the investments, costs of change in the model prevent the time-to-time reassignments of products from one system type to another. As stated earlier, excess modules can be sold, however, their value Ψ is decreased by the depreciation that is calculated according to the common linear formula. By using different resource types for the production over the horizon, this depreciation is minimized by the objective function (Ψ), depending only on the assignments z^s_{pu}. Decision variables g^s_{bu} express the option to assign selected subsets $B \subset P,\ b \in B$ of products to the same system type, in order to utilize the advantages of applying a common resource pool (3.29). This option is valid for reconfigurable and flexible systems, designed to produce several product types economically. In order to avoid nonlinear terms in the constraints (e.g. by introducing nonlinear predictors in the regression functions), these additional variables are introduced, and the subsets are selected when defining the regression models. In this way, complex correlations among the processes of products assigned to the same system can be captured, while keeping the linearity and thus simplicity of the optimization model.

3.4.4 Short-term task scheduling in modular assembly systems

The lowest, operational stage of the proposed capacity management framework is responsible for the short term, fine scheduling and sequencing of tasks in modular systems (Figure 3.12). As highlighted earlier, modular reconfigurable systems are cutting edge in assembly technology, whereas dedicated and flexible systems are commonly applied in industrial practice. Therefore, the formulated task sequencing problem and the proposed solution reflect the main aspects of scheduling with modular reconfigurable resources. According to the problem specification provided in Section 3.2.3, the objective is minimize the total headcount of operators h^{total} required to perform the schedule, by calculating the task execution start t^{start}_n times within the time period t. The main input of the scheduling problem is provided by the higher level production plan, specifying the production lots $n \in N$ to be assembled in t. In order to solve the task scheduling problem, the production planning model introduced in Section 3.4.2, needs to be slightly modified. In case only the strategic and tactical levels of the framework are used for capacity management, the models introduced in the previous sections can be used directly. In case the task scheduling is part of the applied planning workflow, a modified production planning model is applied as introduced below. The reason why two formulations of the planning model exist relies on their different complexity. Whereas the basic model has two decision variables x_{nt} and h_t, the modified version has only a single one x_{ntlh}, however, it is indexed by four sets increasing the problem complexity, compared to the basic model. Results of the models are generally the same as both specify the production lots, however, they differ in the calculation of corresponding human capacities. In the basic model (Section 3.4.2), the headcount of operators is minimized on a period-basis, therefore, it might result in some idle times during the period as only the overall headcount is calculated without the allocation of operators to specific assembly tasks. In contrast, a modified version of the model allows for task-based capacity planning, resulting in a more detailed plan in which operators are assumed to be capable of changing their positions within the planning period. The modified planning model is discussed as it follows in Section 3.4.4.

Modified production planning model

As a first part of the reformulation, it is assumed, that the number of simultaneously operating reconfigurable lines is limited along the horizon by introducing the set of lines L. These lines are "virtual", as they have no static components, but only composed of reconfigurable modules, however, it is assumed that they are placed on a finite set of segments on the shop floor, and each line occupies a single segment. This assumption is required to manage the modular resources in the production planning model, constraining the module-line assignment. Essential part of this model is the novel representation of human capacities in the production planning model by introducing a set of headcounts H, applied to assemble a given product type. The resulting modified production planning problem is formalized as an integer programming model (3.31)-(3.37).

minimize

$$\sum_{l\in L}\sum_{t\in T}\sum_{h\in H}\sum_{n\in N} x_{ntlh}(c^{\mathrm{opr}}h + c_{nt}) \tag{3.31}$$

subject to

$$r_{ltj} \geq r_{jp}x_{ntlh} \qquad \forall\, h\in H,\ j\in J,\ l\in L,\ n\in N,\ t\in T \tag{3.32}$$

$$\sum_{l\in L} r_{ltj} \leq r_j^{\mathrm{avail}} \qquad \forall\, l\in L,\ t\in T \tag{3.33}$$

$$\sum_{\substack{n\in N\\ p_n=p}}\sum_{h\in H} x_{ntlh}(t_p^{\mathrm{rec}} + t_p^{\mathrm{set}} + t_{ph}q_n) \leq t^{\mathrm{w}} \qquad \forall\, l\in L,\ t\in T \tag{3.34}$$

$$\sum_{h\in H} x_{ntlh} \leq 1 \qquad \forall\, l\in L,\ n\in N,\ t\in T \tag{3.35}$$

$$\sum_{t\in T}\sum_{h\in H}\sum_{l\in L} x_{ntlh} \geq 1 \qquad \forall\, n\in N \tag{3.36}$$

$$x_{ntlh}\in\{0,1\} \qquad \forall\, h\in H,\ l\in L,\ n\in N,\ t\in T \tag{3.37}$$

The objective function (3.31) minimizes the overall costs of production. Constraint (3.32) defines the minimal amount of assembly modules to be assigned to line l within a period t, while the total number of modules cannot be exceeded (3.33). Constraint (3.34) states that the total amount of processing and setup times of tasks must be less than the length of a time period t^{w}, for each line l. The last constraints state that only a single operator headcount h can be applied for the execution of each task (3.35), and each order needs to be fulfilled (3.36).

In the basic model, the headcount of operators was determined on the production planning level, therefore, its solution cannot be applied as an input of the scheduling model to minimize the total headcount by scheduling the tasks. Therefore, the decision variable of the planning model was modified to determine the headcount on a task basis, instead of a period basis. This modification requires some pre-calculations, to define the applicable headcount scenarios $h \in H$ for the different tasks, and related headcount-dependent processing times t_{ph}. The applicable operator headcount of the products' assembly processes is bounded by both the required number of modules r_{jp} and the processing times of different elementary assembly operations. The resultant maximal operator headcount is the minimum of these two values (3.38). On the one hand, the operator headcount cannot exceed the number of modules when assembling a product. On the other hand, the operator headcount is also limited by the assembly operations' processing times: if more operators are assembling a given product type p, the resultant cycle time is the linear function of the operator headcount. In the simplest case, one can expect half cycle time for a product when it is assembled by two operators instead of one. This linear correlation is valid until a certain operator headcount is reached, as the resultant cycle time cannot be higher than the longest elementary operation time t^{op}_{pa}, where a is an assembly operation of product p that has $a \in A$ operations in total. The maximum operator headcount in this case is the nearest lower integer of the fraction of total processing time t_{ph} and the longest operation time $\max_{a \in A} t^{\mathrm{op}}_{pa}$.

$$h^{\max}_p = \min_{p \in P} \left\{ \sum_{j \in J} r_{jp}; \left\lfloor \frac{t^{\mathrm{proc}}_p}{\max_{a \in A} t^{\mathrm{op}}_{pa}} \right\rfloor \right\} \tag{3.38}$$

As stated above, assembly cycle times are inversely proportional with the operator headcount. If one had to represent the human capacity constraints in a mathematical model, inequality (3.39) should be applied.

$$\sum_{\substack{n \in N \\ p_n = p}} x_{ntl} \left(\frac{t^{\mathrm{proc}}_p q_n}{h_n} \right) \leq t^{\mathrm{w}}, \tag{3.39}$$

where h_n is a decision variable, expressing the headcount of operators completing the assembly tasks of order n, and x_{ntl} binary variable determines if order n is processed on line l in period t. As it is seen, the fraction term with the decision variable in the denominator would lead to a non-linear model, which is avoidable. Therefore, in order to keep the linearity of the planning model, a new decision variable x_{ntlh} with an additional dimension h is proposed in the planning model instead of x_{ntl}. The above relations are valid only in case of approximated line balances, when the structure of the line as well as the operator task assignments are unknown. Otherwise, if line balances of different operators headcount scenarios are known a-priori, the headcount-dependent processing times t_{ph} can be replaced with the values given by the different line balances. Therefore, the above pre-calculations need to be performed for each product type $p \in P$, and possible operator headcount $h \in H$ to calculate the values of t_{ph}. Using the formula (3.38), one can calculate the set of possible operator headcounts: $H = \{1, \ldots, h^{\max}\}$, where $h^{\max} = \max_{p \in P} h^{\max}_p$.

Task scheduling model

Performing the above modifications on the model and calculating the operator-dependent task times and possible headcounts, the formal model of the considered scheduling problem can be defined as it follows:

minimize

$$h^{\text{total}} \tag{3.40}$$

subject to

$$t_n^{\text{start}}, t_n^{\text{end}} \in \left[t_{p_n}^{\text{set}}, \ldots, t^{\text{w}}\right] \qquad \forall\, n \in N \tag{3.41}$$

$$\left(t_m^{\text{end}} \leq t_n^{\text{start}}\right) \vee \left(t_n^{\text{end}} \leq t_m^{\text{start}}\right) \vee (L_n \neq L_m) \qquad \forall\, n \in N, m \in N, n \neq m \tag{3.42}$$

$$\sum_{n:(t_n^{\text{start}} \leq t) \wedge \left(t_n^{\text{end}} > t\right)} h_n \leq h^{\text{total}} \tag{3.43}$$

The objective function (3.40) states that the total headcount of operators working in the period is to be minimized. The first constraint (3.41) defines that the execution start t_n^{start} and end t_n^{end} times of task n (also considering the setup time of the assembled product) are bounded by the duration of a period. The second constraint (3.42) states that only a single product type can be assembled on any given virtual line $l \in L$ at any point of time. The last constraint (3.43) specifies that the total operator headcount must be greater or equal to the sum of operator headcounts assigned to the executed tasks at any point of time. In (3.43), the headcount h_n of operators assigned to task n is defined as $h_n = \sum_{h \in H} \sum_{l \in L} x_{ntlh}$, if $t \in T$ is the time period of the scheduling problem to be solved.

Task scheduling with constraint programming

Production scheduling problems —similar to the one presented in Section 3.4.4— are often solved by constraint programming (CP) techniques, enabling to find feasible schedules in a reasonable time. The strength of constraint programming relies in the high level, descriptive modeling approach, and the efficient handling of various constraints even in large scale problem instances. Constraint programming has two core elements: a set of predefined constraint types (constraint store) and a built-around programming language to instantiate and combine the constraints (Hentenryck, 1999). In practice, CP solvers combine constraint reasoning and non-deterministic search approaches to find the solution for a specific problem (Hentenryck and Michel, 2009). Constraint reasoning involves various filtering steps for domain reduction, in order to consider and satisfy multiple constraints that share common variables, this procedure is called constraint propagation (Bessiere, 2006). For scheduling problems, constraint programming solvers offer various domain-specific filtering algorithms, called constraint propagators.

The scheduling problem —introduced in the previous section— can be solved by using the cumulative and disjunctive resource propagators. Cumulative resources are represented by their capacity, and the tasks need to be scheduled so as their total utilization of cumulative resources cannot exceed resource capacity C at any point of time. Therefore, operators (3.43) in the formulated CP model are represented as cumulative resources of a single type, and their capacity is exactly the objective function h^{total} of the model. The second, called disjunctive resource propagator is a special cumulative resource, whose capacity is $C = 1$. In the considered scheduling problem this means that any two tasks assigned to the same line L cannot be scheduled so that their executions overlap in time (3.42), therefore, lines are represented as disjunctive resources. Concluding the aboves, one can infer that formulation of the problem with CP techniques — applying cumulative and disjunctive resource propagators— is straightforward, however, neither the stochastic nature of manual processing times, nor the random events can be considered with this modeling technique.

Task scheduling with genetic algorithm

For the above reasons, the problem is also solved by genetic algorithm (GA), which is one of the most fundamental approaches to solve stochastic optimization problems. Genetic algorithms are classified as search metaheuristics belonging to the class of evolutionary algorithms. Applying bio-inspired genetic operators on a set (population) of candidate solutions (individuals), GAs try to improve the solutions and move towards the global optima. Similarly to other global optimization methods, hurt of the constraints in GAs is mostly penalized with extra costs in the objective (fitness) function. Generally, genetic algorithms are capable of handling stochastic parameters if one can evaluate a solution considering them. Consequently, they can be applied to solve the considered scheduling problem where stochasticity characterize the parameters due to the manual processing times with certain deviations, and other random events like scrap products entailing rework. A simulation-based method is proposed to evaluate a solution: the fitness function of a given schedule is determined by executing a discrete-event simulation analysis. This approach allows for the detailed analysis of stochastic parameters that often characterize manual assembly processes. In each iteration of the GA, simulation experiments are executed to evaluate the individuals' fitness, therefore, the time consumption of a single simulation run is of crucial importance to keep the algorithm's overall running time on a reasonable level. The simulation applies an automated model building process, enabling the dynamic model creation and realistic handling of resource constraints (Gyulai et al., 2012).

3.5 Hierarchical capacity management: experimental results

The proposed method is evaluated with the results of a real industrial case study from the automotive sector. The company under study is a *Tier-1* supplier, producing mechatronics components to several OEMs. In its assembly segment, the company has to manage the production of $|P| = 67$ main product types, characterized with very diverse yearly volumes and uncertainty in the forecasts. Due to the high costs, limitations in shop-floor space and in skilled human workforce, finding an optimal capacity management policy would result in significant benefits for the company. In the analyzed case, modularization is based on a set of standard assembly processes (e.g. manual screwing, pressing, greasing etc.), assigned to technological assembly modules $j \in J$. In this way, it is assumed that each product can be assembled in a modular assembly system with the desired quality, independently from the resource type. Although the product portfolio is rather diverse, the whole set of assembly operations can be categorized in eight main types (e.g. screwing, pressing, greasing etc.), therefore, the operations can be performed by a module set of $|J| = 8$. As the assembly processes are simple and the products are relatively small-sized, lightweight *plug-and-produce* modules can be applied in the assembly system.

3.5.1 Approximation of the costs with regression models

In order to analyze the costs characterizing the operation of flexible and reconfigurable systems, the tactical production planning model was solved first on a set of virtual scenarios. These scenarios were generated and solved in *FICO Xpress®* optimization software, applying its built-in mixed-integer programming solver engine[1]. In each virtual scenario, input data was generated randomly by the following rules. The length of planning horizon was $|T| = 40$ production periods, the number of orders were $|N| = 1 \dots 350$, and order volumes were $q_n = 1 \dots 800$ per order. These parameters provided a representative set of various virtual but realistic order stream scenarios, including both easier and complex planning problem instances. The production planning problem (Section 3.4.2) was solved 450 times for each resource type $s \in S$. Then, the resulted datasets were split up into independent training and test sets, applying random sampling with 1:2 ratio. Accordingly, the regression models were all defined over the training datasets including 150 observations, and evaluated with the test sets consisting of 300 observations. Based on the proposed method, eight regression models were defined in total: two for the value of assets λ_u^{s}, three for the volume costs Γ^{s} functions, and three models to predict the operator requirements (3.25). In each model definition, forward stepwise method was performed in feature selection, and nonnegative linear regression with the `nnls` package —implementing the *Lawson-Hanson algorithm*— was applied in order to avoid unrealistic function approximation with possible negative coefficients (Mullen and van Stokkum, 2012). The main fit properties of the regression models are summarized in Table 3.1.

Table 3.1. Fit properties of the regression models defined for the dedicated, flexible and reconfigurable system types $S = \{d, f, r\}$.

	S	Notation	R^2	F-stat.	p values
Volume	d	Γ^d	0.91	2779	~ 0
Investment	f	λ_u^f	0.71	182	~ 0
Volume	f	Γ^f	0.92	1329	~ 0
Investment	r	λ_u^r	0.77	250	~ 0
Volume	r	Γ^r	0.94	4963	~ 0
Op. req.	all		~ 0.95		~ 0

As for the predictor variables, the total forecast volumes f_{pu} were applied to determine the volume costs. These models tackle the nonlinear interactions among products, applying the product subset variables g_{bu}^s as stated in Section 3.4.3. In the presented case, nine subsets were applied; and products were selected during the model fitting procedure:

$$\Gamma^s = \beta_{s0}^{\mathrm{vol}} + \sum_{u \in U} \sum_{p \in P} \left(\beta_{sp}^{\mathrm{vol}} z_{pu}^s f_{pu} \right) + \sum_{u \in U} \sum_{\substack{b \in B \\ b = p}} \left(\beta_{sb}^{\mathrm{vol}} g_{bu}^s f_{pu} \right) \quad \forall\ s \in \{r, f, d\} \tag{3.44}$$

In the case of flexible and reconfigurable resources, prediction of the value of assets λ_u^s was done, based on the number of assigned products and the total capacity requirements:

$$\lambda_u^s = \beta_{s0}^{\mathrm{fix}} + \sum_{p \in P} \left(\beta_{s1}^{\mathrm{fix}} z_{pu}^s + \beta_{sp}^{\mathrm{fix}} z_{pu}^s f_{pu} t_p^{\mathrm{proc}} \right) \qquad \forall\ s \in \{r, f\},\ u \in U \tag{3.45}$$

[1] All the computational experiments presented in the thesis were performed on a laptop with 8GB RAM, and Intel® Core i5 CPU of 2.6 GHz, and under Windows 8.1 64 bit operating system.

The headcount of operators in a given period $u \in U$ was approximated by the sum of capacity requirements in u and $\forall s \in S$ as formulated in (3.25).

3.5.2 System configuration study

Introduction of the compared methods

In industrial practice, firms usually solve the configuration problem of heterogeneous systems (supposing that different resource types are available, see Section 3.2) on a product basis, neglecting the underlying correlations among the assignment of different products to the same resource type. Reflecting to the line assignment problem presented in 3.3.2, decisions of the workflow were also taken on a product basis, however, future expected production costs were predicted by considering tactical level production planning aspects. In product-based approaches, system designers seek the proper system configuration by combining the main advantages of different resource types in a straightforward way, therefore, top-runner products with high yearly volumes are mostly assigned to dedicated resources that are capable of providing the desired throughput rate. Flexible resources are applied to produce medium-runner products with similar features and volumes, meanwhile, low-runner products with low yearly volumes and high variety typically preferably assigned to modular, reconfigurable systems. The latter products are mostly the prototypes, end-of-lifecycle products, or spare parts for aftermarket.

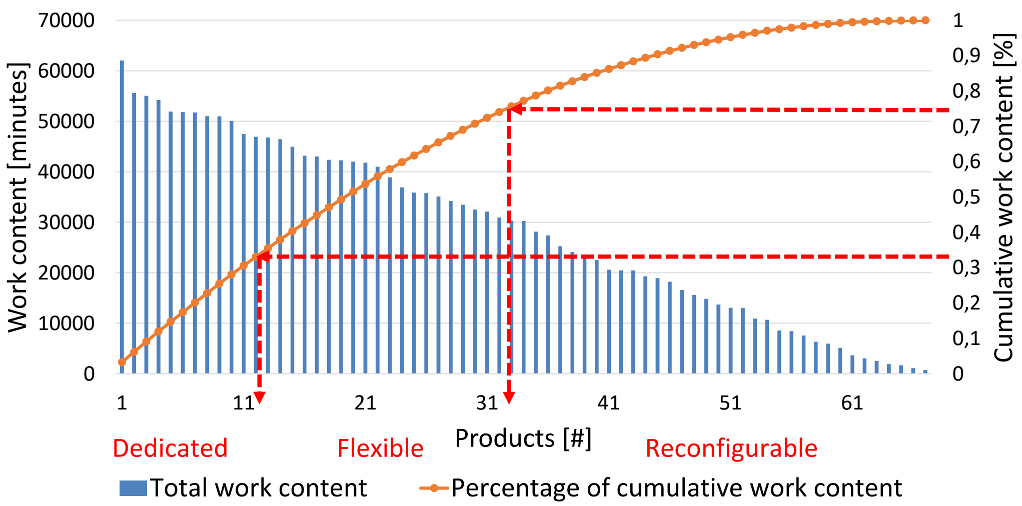


Figure 3.13. Representation of the *CR* rule on the Pareto-chart of the products' work contents.

As no specific optimization-based method is available to solve the analyzed problem (Section 2.4), the proposed capacity management workflow was compared to the above described, rule-based practical method within a comparative study. Four different methods were analyzed by solving the system configuration problem over multiple periods. The product-based solutions applied in industrial practice were represented by rule-based approaches that assign the products to different resource types based on the total work contents. In the study, two rule-based methods were compared to the proposed method. According to the first rule called *CR*, the product portfolio was split up with different ratios in three parts, based on the overall work contents realized in each period. The products were then assigned to dedicated, flexible and reconfigurable systems, respectively. Important feature of this rule that splitting was done based on the cumulative work contents of the products, meaning that not individual capacity requirements percentages were considered, but products were sorted in a descending order according to their total capacity requirements, and cumulative percentages were applied to assign products to different resource types. This method is depicted by an exemplar Pareto-chart of work contents in Figure 3.13. In the second rule-based method called *IR*, individual percentage values of the products' work content were considered, when assigning them to different resource types. In this case, two threshold values were defined: the products with lower, average, and high work contents (defined by the threshold values) were assigned to reconfigurable, flexible and dedicated resources, respectively.

The proposed, optimization-based system configuration method —that is part of the framework— was also implemented in two different ways within the study: the first version —called *LO*— considered a fix horizon, and determined the best system configuration strategy by looking ahead in time over the entire horizon. The second version implemented a rolling horizon system configuration strategy by periodically (in the test case, the re-planning period was $2u$) updating the actual configuration in the upcoming periods. The latter method —called *RO*— considered shorter planning horizon than *LO*, however, the strategy was updated in shorter periods than this horizon. As for the time horizons of the rule-based *CR* and *IR* methods, both based on a rolling horizon approach similarly to the *RO* method. The difference between the planning horizons and replanning periods of the lookahead and rolling horizon methods are illustrated by Figure 3.14.

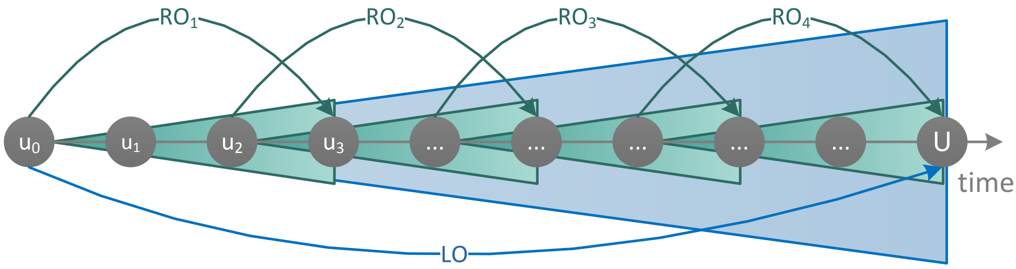


Figure 3.14. Representation of the replanning periods (arrows), and time horizons of the rolling horizon *RO* (green), and lookahead *LO* (blue) methods with the confidence regions of the volume forecasts (triangles).

Scenarios of the study

The system configuration problem was solved on a planning horizon consisting of $|U| = 10$ periods, on which volume forecasts were available, however, they were uncertain as realized order volumes in period u might differ by 10% from the volumes predicted in $u-1$ (confidence regions are represented in Figure 3.14). Therefore, weighted averages of the forecast volumes f_{pu} were applied in the system configuration problem, with five periods lookahead. In each period u, decision variables z^s_{pu} were determined based on the forecasts, and the necessary investments were calculated. Then, the production planning model was run to predict the costs that will incur in period u. In this case, the cumulated forecast volumes were split into customer orders, simulating maximum 10% deviation (normal distribution) in the total volumes by generating individual orders $n \in N$ with random assigned (with a realistic, uniform distribution over the horizon) due dates t^{d}_n and order volumes q_n. In order to avoid infeasibility of planning, an additional time period $t \in T$ was added to the end of the horizon, with infinite length and high assignment cost to simulate the option of backlogging (this modification was applied when solving the models on virtual scenarios in section 3.5.1).

Within the study, scenarios were characterized by two main factors: the nature of the products' lifecycle and the art of the product portfolio. As for the lifecycles, two cases were analyzed. In the first case called *normal (NORM)*, products' lifecycle were similar to a general product lifecycle curve with the introduction, growth, maturity and decline phases, and products of the portfolio were in different stages of their lifecycle. This case is represented by products with increasing, decreasing and relatively stable volume trends, applied for randomized order and forecast generation. This scenario is valid for the majority of companies, however, there exist companies who suffer from frequent changes in the customer orders, which means that the volumes to be produced have no general trend. This is represented by the second case of the product lifecycle called *volatile (VOL)*, which analyzed order streams where significant volume changes might occur between two consecutive periods.

The second major analyzed factor was the diversity of product portfolio that can be either balanced or diverse. In case a portfolio is diverse *diverse (DIV)*, significant differences can be among the total capacity requirements of products in a given time period: there are products ordered in very high volumes and/or having high total processing times, and also products with very low work contents and/or volumes. In case of *balanced (BAL)* portfolio, the total work contents of products are similar (the volumes of processing times can be diverse, but the overall capacity requirement are in the same order of magnitude).

As several realistic production and market scenarios are analyzed, some random generated input parameters are applied based on a general input data. The following main rules are valid for different scenarios, and more detailed description of the scenarios' input data, and the generation of random parameters is provided by Gyulai (2018):

- Products' lifecycle curve:
  - Normal ($NORM$): The products' lifecycle follows a monotonic increasing or decreasing trend with an average of 10-30% difference in total volumes between two consecutive periods.
  - Volatile (VOL): There is no trend in products' lifecycle, and the average difference in total volumes between two consecutive periods is 30-50%
- Diversity of the product portfolio:
  - Diverse (DIV): The products' relative, total capacity requirements uniformly distribute between 1-100%.
  - Balanced (BAL): The products' relative, total capacity requirements uniformly distribute between 1-10%.

The above settings resulted in four main scenarios (the combinations of the above factors) that were all analyzed within the study. In each scenario, 15 different test cases were generated with similar main attributes, however, with different customer orders and product lifecycle characteristics. As for the experiments, in case of *CR* and *IR* methods, six-six different assignment policies were applied, which differed in the percentage threshold values. Therefore, the total number of experiments in the study was $15 \cdot (1 + 1 + 6 + 6) \cdot 4 = 840$ in case of the system configuration. As $|U| = 10$, the production planning problem —to evaluate the costs in each periods— was solved 8400 times in total.

Discussion of the results

The main numerical results[2] of the study are summarized in two boxplot charts (Figure 3.15-3.16). For the sake of comparability, both charts represent the results in percentage values. The percentages are calculated by considering the results obtained by the four different methods in a given test case, and 100% corresponds to the maximal value in each test case, thus in general, lower values are the better. Columns of the boxplots visualize the average, maximum and minimum values, as well as the percentiles of 15 test cases per scenarios and methods.

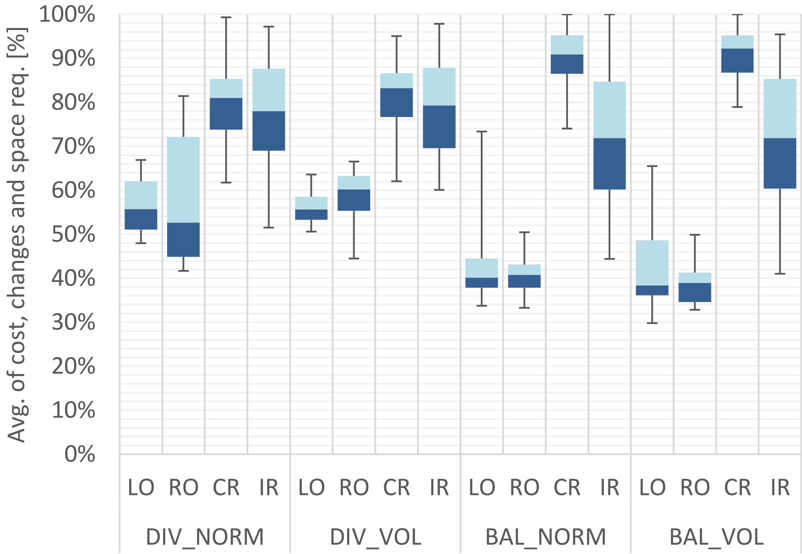


Figure 3.15. Results of the case study: average values of the resulted costs, changes (3.22) and space requirements (3.24).

The first boxplot (Figure 3.15) visualizes average results including costs, space requirements, and changes realized over the planning horizon with a given method. In contrast to the proposed solution, rule-based system configuration methods were unable to consider several constraints, therefore, the space limit as well as other restrictions might hurt when applying such methods. These factors are also summarized in the first comparison illustrating that LO and RO methods outperform the rule base approaches in most of the cases. While in case of diverse portfolios and normal lifecycles, IR method might perform satisfactory, the difference between the methods increases if hectic lifecycles or balanced portfolios are analyzed. Although lookahead LO method performed well in average, rolling horizon based RO showed much stable good performance with low deviation in each cases. Summarizing this comparison, the performances of rule-based solutions were similar to the proposed approaches only in case of normal product lifecycles and diverse portfolios, however, they still resulted in higher costs in average, moreover, deviation of the results was also rather high.

In contrast to the previous boxplot, Figure 3.16 summarizes only the overall costs obtained by the different system configuration methods. The most obvious difference here is the high deviation of the costs resulted by the LO method, caused by the fact that space limits and number of changes are neglected here, therefore, the results of rule-based methods are comparable to the optimization-based ones'. Although LO method resulted in high deviation in these cases,

[2] The complete, detailed set of numerical results, the implementation of the models and the input data for reproducibility of the research are provided in a GitHub repository: `https://github.com/dgyulai/ModularAssembly`

the average of solutions were still better than those obtained by rule-based solutions, while RO approach with a rolling horizon assignment performed best in each scenario. It resulted in the lowest average total configuration costs, moreover, it had the most stable performance with low deviation in the solutions.

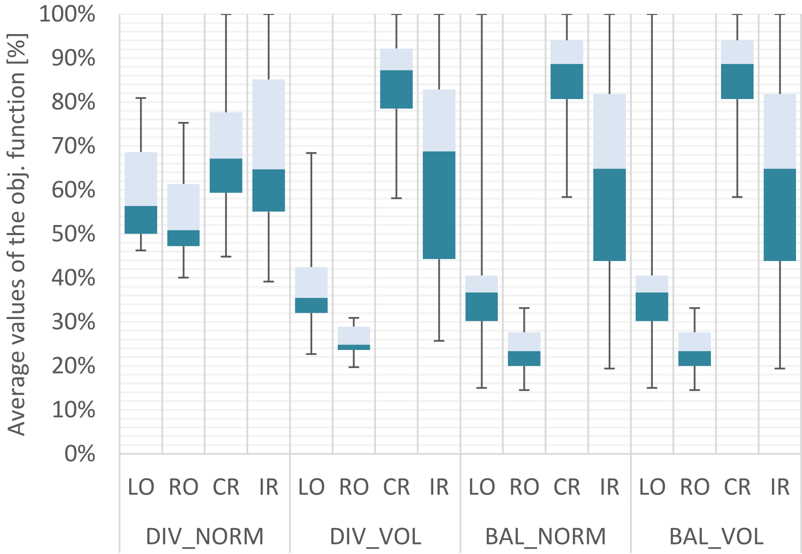


Figure 3.16. Results of the case study: overall costs (3.22).

Summarizing the results of the case study, one can conclude that the performance of rule-based approaches is inversely proportional with the uncertainty (hectic lifecycle), and their results' quality is decreasing if the portfolio is composed of products with similar total capacity requirements. In those cases, general practical approaches become unstable, as the calculated system configuration cannot cope with the uncertainty of forecasts, nor with the frequent re-assignments of products to different system types. Besides, it is also unclear which rule needs to be applied in a given case, as their performance is highly influenced by the parametrization that cannot be done in advance. In contrast, the proposed, optimization-based solution outperforms the currently applied product-based assignment and system configuration methods by considering portfolio-wide correlations among the processes, and optimizing assignments along the horizon accordingly. The best results, thus the lowest overall costs can be obtained if the method is applied on a rolling horizon basis, revising and updating the applied configuration periodically.

3.5.3 Numerical results of task scheduling

In the previous analysis, both system configuration and production planning models were solved within a case study with the aim of configuring a modular assembly system on a longer horizon, considering predicted costs based on multiple solutions of production planning problem. Next, the operational level model of the hierarchical capacity management framework was demonstrated, solving the short-term task scheduling problem. Within the analysis, production environment remained the same, however, the modified production planning model was solved to provide input for the subsequent task-scheduling. The latter was solved by both CP and GA, and their results were compared according to robustness criteria.

Parameters of the task sequencing problem

As discussed earlier, the modified production planning model is aimed at calculating the lot sizes with the assigned line and operator headcount (x_{nlth}) based on the customer order stream and available capacities. The planning horizon is $|T| = 10$ periods, and the length of a period is $t^{\mathrm{w}} = 480$ minutes. In the analyzed problem instances, the total number of orders to be scheduled varies in a range $|N| \in [120, 150]$ on the complete planning horizon T. The available shop-floor space in the assembly segment enables to operate $|L| = 8$ modular lines simultaneously. Calculating the headcount-dependent processing times for each product type p, the maximal headcount of operators and thus the cardinality of their set is $|H| = 10$. As for the scheduling problem, the task is to determine the task execution start t_n^{start} (and end t_n^{end}) times within the periods, considering that the setup times of the products are $t_p^{\mathrm{set}} \in [15, 30]$. Resulting from the production planning level, the average size of a scheduling problem instance is $|N| \in [12, 15]$ within a given time period t. In order to prove the validity of the proposed mathematical models and compare the solutions provided by CP and GA, eight different test problem instances were solved by both methods. First, the production planning problem was solved, afterwards eight different production periods from the results were selected to solve the task sequencing problem.

Table 3.2. Comparison of scheduling results, provided by CP and GA methods. The first column (SC) indicates the scenario number, $|N|$ is the number of tasks (orders) to be scheduled in one selected time period. The columns h^{total} give the resulted headcount and t is the running time in seconds. The last columns t_m are the makespan values (minutes) of the methods, and t_m is the calculated whereas t_m^{sim} is the simulated makespan (of the CP solution).

		Constraint programming				Genetic algorithm		
SC #	$\lvert N \rvert$	h^{total}	t[s]	t_m[min]	t_m^{sim}[min]	h^{total}	t[s]	t_m[min]
1	15	11	3	471	488	12	172	427
2	14	8	2	469	502	8	567	433
3	11	7	601	476	476	7	328	448
4	16	7	5	475	477	7	175	471
5	15	7	4	480	470	7	558	469
6	14	8	3	477	506	8	158	508
7	11	6	2	470	466	6	247	433
8	11	7	603	457	493	7	457	497

Results with constraint programming

The CP model of the task scheduling problem —specified in Section 3.4.4— was implemented in *FICO® Xpress* applying its *Kalis* constraint programming library with a scheduling toolbox. In order to handle the resource constraints properly, the assembly lines $l \in L$ were disjunctive, while the operators were cumulative resources with the capacity of h^{total}. By default, the constraint solver cannot be set to optimize the production schedule respecting the capacity of resources as an objective function. Therefore, the optimization procedure was performed by an iterative approach with interval halving, where the value of h^{total} was adjusted in each iterations. Starting with and arbitrarily large value, the problem was solved in each iteration, and the value of h^{total}

was decreased to its half if a solution was found. Otherwise, the headcount was set to the median of current and previous values. In this way, the objective function value converged to the solution, while feasible schedules could be obtained over the iterations. In order to boost the computations, the CP solver run until a feasible schedule has been found. All problem instances could be solved by CP, calculating the minimal required operator headcount and the corresponding feasible schedule, however, all parameters of the model were deterministic as CP solver could not tackle their possible variability.

Results with a genetic algorithm

For this reason, the scheduling problem was also solved by GA, as considering the possible stochasticity of the parameters is important in case of manual assembly lines, where the *human factor* introduces a certain deviation in the processing times. Therefore, the emphasis was put on this effect by setting 10% deviation for the manual processing times with a normal distribution. This could be done in the simulation model of the assembly system, which was also responsible for the evaluation of a solution in each iteration of the GA. In order to get a more realistic solution, each individual (schedule) in the population was evaluated by running the simulation multiple times simulating different processing times generated with a normal distribution with 10% deviation by the simulation model. The schedules were created by the algorithm applying genetic operators, in the GA, the main settings were the probabilities of crossover and inversion steps', set to 0.8 and 0.2, respectively. The number of iterations was set to 20, and the population sizes were 15. The simulation model of the assembly system was implemented in *Siemens Tecnomatix® Plant Simulation*, applying its GA library with the predefined chromosome encoding of the *GASequence* function (Siemens, 2016). The resources (both human and machine) were represented by objects in the model, each having disjunctive feature enabling to tackle the capacity constraints in the GA-solution.

Evaluation of the results

In order to evaluate the quality of solutions and the feasibility of schedules, the results provided by both methods were executed with the simulation model of the system, representing the 10% deviation of the processing times. In order to manage this stochasticity in the CP scheduling model and to calculate feasible schedules with it, the processing times were increased by 10% in the CP, while in GA, all the evaluations were performed by the simulation model applying the same deviation. The results provided by both methods for all analyzed problem instances are summarized in Table 3.2. As the results show, the running time of the GA is significantly higher than that of the CP, however, it results in the same objective function values except in SC#1. The GA-based solution provides schedules that are feasible in most of the cases, even in case of stochastic processing times, whereas CP fails to provide executable schedules in more cases if parameters are stochastic, although the schedules were calculated with extra capacities. In each cases, the CP could provide a schedule that would be feasible with deterministic parameters, however, lateness occur in the simulation, representing the realistic production environment (Gyulai et al., 2017a).

3.6 Summary of Chapter 3

The existence of heterogeneous assembly systems with reconfigurable, flexible and dedicated resources is a relevant industrial topic, however, only a few approaches are available for comprehensive capacity management of these systems. In Chapter 3, a novel hierarchical method was proposed for modular assembly systems, with the objective of minimizing the operating and investment costs along the lifecycle of the products. The framework has three stages, providing solution for the capacity planning problems on all levels of the classical planning hierarchy. The essential novelty of the method is realized by the fact that operation and investment costs are approximated with regression functions that are directly applied in the optimization model of the system configuration problem. Moreover, system configurations are determined based on the entire portfolio considering the correlations among processes. In addition to the strategic and tactical levels of the capacity management, the task scheduling problem —related to modular reconfigurable systems— is solved on the lowest stage of the framework. The proposed scheduling model determines the operator-task assignments, as well as the execution start times of the production lots. The input parameters of the scheduling are provided by the production planning model, and its objective is to minimize the overall operator headcount within a production period.

The proposed method results in significant cost savings in the long run, compared to the most commonly applied rule-based approaches. This is mainly resulted by the consideration of future expected production costs already in the configuration (and periodic revision) stage of the assembly system. The operational costs are determined with regression models, implementing a function approximation based on tactical level production scenarios. The functions are applied in the strategic level system configuration model as constraints and as elements of the objective function, too. The applicability of such regression models in higher level decision models was proven by a simplified version of the capacity management problem called line assignment. In the line assignment model, products were assigned to dedicated, reconfigurable resources or outsourced, and the decisions were taken on a product basis. In this proof-of-the-concept decision method, the costs resulted by production plans of virtual scenarios and fed back in the line assignment model with regression models. The results of product-based assignment indicated that such regression-based feedbacks are capable to be used in more complex, portfolio-based system configuration model.

In the three-level framework, the artificial set of random-generated virtual scenarios provide representative data of costs that need be considered when deciding about system configuration, and assigning the products to different resource types. The proposed framework puts special emphasis on the capacity planning of modular, reconfigurable assembly systems with lightweight plug-and-produce resources that are hardly considered in other capacity management methods and models. The production planning model applies constraints on machine resources that are specific to the system type, additionally, the human resources are also considered providing flexibly-adjustable capacities for the system. Slightly modifying the basic production planning model of the modular reconfigurable system, the human capacity requirements can be optimized on a task basis by solving the task sequencing model.

Besides the above facts, great benefit of the method is its practical usage for real industrial sized problem instances, characterized with a large product portfolio and frequent changes in it. The results of the case study proved that capacity management problems —even with different resource types and several products— can be solved in a reasonable time. As for the integration of the method in existing corporate decision processes, one can conclude that strategic level system configuration decisions are effected independently from enterprise software tools, therefore, the method can be applied directly for decision support even having a loose link with other tools. Besides, generic mathematical models were proposed to solve the production planning and task scheduling problems, therefore, they can be implemented in any solver, respecting the resource constraints of the modular systems as described in the chapter.

Chapter 4

Capacity management of modular, robotic assembly cells

In the previous chapter, a novel, comprehensive framework for the capacity management of modular assembly systems was proposed. The framework was aimed at matching the capacities of modular system with customer order stream on the strategic, tactical, and also on the operational levels of the planning hierarchy. The production environment consisted of a modular assembly system with heterogeneous resources, of which reconfigurable modules supported the fast reconfiguration of the system, utilizing the lightweight, plug-and-produce workstation design. In case assembly modules are applied to carry out the processing of heavy workpieces, or the assembly technology requires large-size equipment, lightweight assembly modules cannot be used to configure the system. However, the state-of-the art in assembly technology has made it possible to apply reconfigurable assembly cells in industrial practice (Manzini et al., 2004). In general, cellular manufacturing is an important application of lean production and group technology, in which part families are produced in manufacturing cells or a group of various machines, which are physically close together and can entirely process a family of parts (Mansouri et al., 2000). In case of assembly application, reconfigurable cells can be built up of modules that can perform automated joining processes like resistance spot welding, gluing or hemming. This assembly cell design provides flexible solution to assemble products with larger dimensions (e.g. car body parts), even if facing high variety in the product portfolio.

In Chapter 4, a new, integrated framework for the capacity management of modular reconfigurable assembly cells is introduced, aimed at offering a comprehensive solution to support design and management related decisions. As the framework is the result of a collaborative work, the special emphasis is put on the own work that is the production and capacity planning of the cells, supporting the configuration stage of the workflow by predicting the future expected operation costs and batch sizes. Next to the planning and simulation, the core architecture of the software integration environment —called *Simulation and Navigation Cockpit*— is also presented. The cockpit provides a web-based software environment to link the individual tools with each other, customize the parameters and display the experimental results.

For the sake of completeness and demonstration, all stages and tools of the workflow are introduced, however, own results related to production planning and simulation are highlighted and discussed in detail. Other works and models presented within the framework are results of academic partners participated in the *RobustPlaNet* EU FP7 project. The overall concept, methodology and results were presented by the partners in collaborative papers (Colledani et al., 2016; Manzini et al., 2017). The framework consists of four main tools with the corresponding decisions and problem instances. The first tool, called *Assembly System Configuration Tool* is developed by the University of Twente[1]. The second tool, called *Assembly Cell Configuration Tool*, and the *Reconfiguration Planning Tool* —incorporating and utilizing the results of all other tools— are developed by Politecnico di Milano[2]. The own results were achieved in the definition and development of the *Production Planning and Simulation Tool*, presented in detail in Sections 4.4.2-4.4.3.

4.1 Design and management of modular assembly cells

As discussed earlier, the capacity management of modular reconfigurable assembly systems is an emerging research topic, as the application of technological modules as building blocks of assembly systems is gaining more and more attention in today's production. This is valid for the lightweight assembly modules, and also for the large-size modular resources of automated cells, capable of performing various joining processes. In contrast to the lightweight assembly modules, high technological and quality requirements are more complicated to achieve with the joining modules, as several various parameters affect the quality of final products. In addition to, another challenge to be tackled by the system designers is the increasing variety and complexity characterizing the joining technology. These challenges have increased side effects on the supplier companies, as they have limited time to respond OEMs' requirements, moreover, they do not have the opportunity to apply changes and modifications on the products and technologies that would make it easier to introduce new products in the existing portfolio and the corresponding assembly system. In the presented methodology, automotive supplier companies are mainly considered, who are involved in the production of new parts in their ramp-up phase, and also in complementing the OEMs' production capacity for low volume car model niches or to help managing demand peaks. In order to keep their internal efficiency, and meet the customers' requirements, supplier companies tend to increase the flexibility —regarding both mix and volume— of applied production technology. As the product portfolio is continuously changing with the introduction and decline of products, the system structure also needs to co-evolve with the products and processes to maintain the desired level of internal performance indicators.

Although various approaches exist for the design and planning of assembly systems, there is no all-encompassing method that can cope with the above challenges in the design, configuration and operation management tasks emerge in relation to the modular reconfigurable assembly cells. Therefore, a new framework is proposed to support the above decisions, applying different tools and models with their specific problems to be solved on a certain time horizon. As mentioned earlier, the approach entails four tools supporting the following decisions: (i) definition of the system's architecture and multi-cell configuration, (ii) selection of the cell's detailed layout configuration and assembly process operations, (iii) production planning and evaluation of the cell's operation and (iv) major reconfiguration steps that have to be taken between the time periods. The tools can be used in a sequence, to design an assembly system and define the

[1]Corresponding researchers are Johannes Unglert and Juan Manuel Jauregui Becker from University of Twente, Enschede, The Netherlands

[2]Corresponding researchers are Massimo Manzini, Marcello Urgo and Marcello Colledani from Politecnico di Milano, Milan, Italy

associated management policies. In this way, the workflow allows to incrementally increase the level of details and gain additional knowledge about the system, moreover, feedback loops are implemented between the tools, to improve the design or manage possible infeasibility. The integration of decision-support tools aims at providing a robust solution that able to cope with the co-evolution of the system together with products and production technologies. In this fashion, the configuration, layout and reconfiguration of the system consider long-term decisions, while the planning of production and setups addresses the short-term horizon.

Based on the above main characteristics of the proposed workflow, one can distinguish three related sub-problems addressed: system design, cell configuration and the corresponding task sequencing and finally, the production planning and simulation. Although state-of-the-art solutions exist for all these problems individually, none of the approaches integrates them, therefore, they are not capable of providing solutions that provide cost efficient production over the entire lifecycle of the system operated in a dynamic environment. Similarly to the assembly system consisting of lightweight modules, precise estimations of the operation indicators such as costs, setups and batch sizes are of crucial importance to provide a design that can be operated efficiently even if medium or short term objectives and conditions are considered. This can be achieved only with a foresight in design, namely to apply a methodology that performs the medium-term rough production planning to predict the resulted costs. In the design phase of a system, performance is often estimated by considering the bottlenecks operations, disregarding other influencing factors, e.g. the expected production sequences and the resulting changeovers. These factors might have significant impact on the performance indicators in assembly systems, where long setup times occur due to the processes, or the applied equipment (e.g. assembly modules with large sizes).

As a conclusion of the above thoughts, proper management and operation of reconfigurable systems can be achieved only if multiple criteria are considered already in the early design stage of the system. Naturally, this can be hardly implemented due to the uncertainties, and lack of detailed information about the future changes in the order stream and processes. Therefore, the coordinated evolution of system, products and processes is aimed to be supported, in order to revise, and periodically adjust the system configuration respecting external factors. In this way, the efficiency can be maintained while production also matches the customer expectations. Towards the definition of the design and management framework proposed to implement this co-evolution, the problem of reconfigurable assembly cell design is presented as it follows in Section 4.2.

4.2 Reconfigurable assembly cell design problem

In general, the problem in question is similar to the system configuration and capacity management problem analyzed in Chapter 4, namely to define a (re-)configuration strategy for a modular assembly system on a longer term, to meet the customer requirements while minimizing the overall related costs including investments as well as operation costs. However, the same methodology cannot be applied here, due to the different system structure, and the fact that only reconfigurable cells are considered (dedicated and flexible resources are not part of the problem). Moreover, the assembly technology and also the products justify that lightweight assembly modules cannot be applied to configure the system, but the considered set of joining technologies includes welding, gluing, hemming, clinching etc. operations performed by automated devices, and/or robots, requesting longer reconfiguration times than lightweight modules. Similarly to the previous case, a group of technological equipment $j \in J$ is selected to perform the processes. Due to the technological complexity, a module is considered to include more pieces of equipment, e.g. the tools, fixtures and control units to accomplish the assembly operations of a product. The requirements of products $p \in P$ from different modules is denoted by r_{jp}, the purchasing costs c_j^{m} of the modules, and also the relevant technological parameters are known. A given assembly operation can be executed in different ways applying a certain module, therefore, the set of possible options an operation can be performed is provided by introducing the set of execution modalities E, for which examples are presented later in this chapter.

Due to the cellular architecture, characteristics of the reconfigurable system differs from the one analyzed in Chapter 3. The modular reconfigurable assembly cells consist of two parts: the static *skeleton* of the system, and also the mobile, exchangeable *technological modules*. The skeleton of the system includes safety equipment such as the fences, and also technological devices like conveyor belts and buffers. Besides, essential central element of the cells is a 7-axis robot installed on a track, enabling very flexible operations including part manipulation, technological processing, as well as material handling. Besides, assembly modules can be attached to the skeleton to perform the assembly operations. As the technological modules are rather heavy, they are transported and placed by forklifts. Relying on this, a limited set of alternative layouts exist, composed of the central rail with the 7-axis robot, and the modules placed around (including the part I/O stations with the conveyor belts). A the general scheme of the considered modular, reconfigurable assembly cell is illustrated by Figure 4.1.

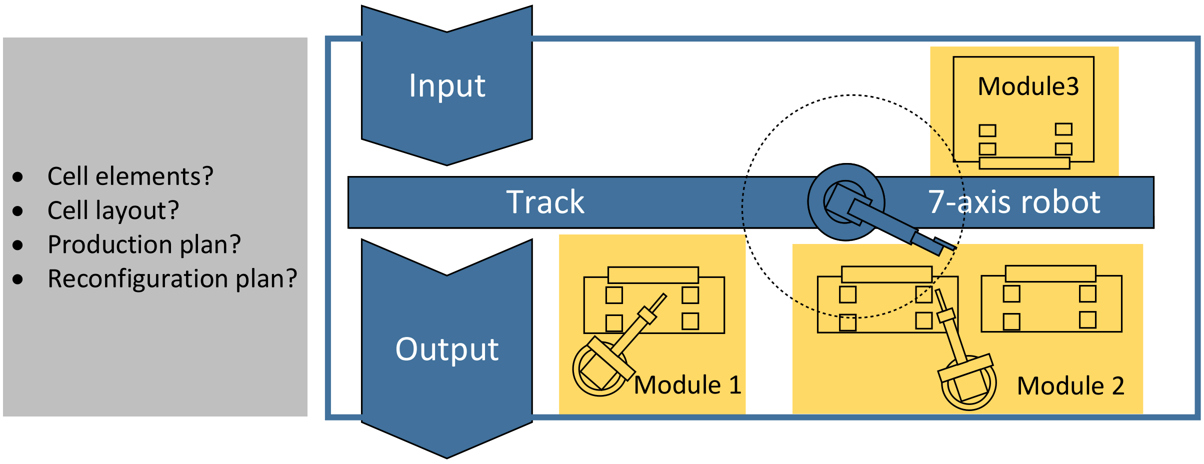


Figure 4.1. Schematic architecture of a modular, reconfigurable assembly cell with the elements of the static skeleton (blue) and the exchangeable technological modules (yellow).

A configuration of a cell $c \in C$ in a period $u \in U$ is represented by a variable z_{cu}, expressing implicitly the applied set of modules and their positions in the layout, the applied tools and selected execution modalities. The objective of the overall approach is to determine the optimal configuration of cell $c \in C$ over the time horizon U, by minimizing the cells' lifecycle costs composed of investment and operation costs factors. This can be achieved by a periodic revision of the cell's actual configuration, and its adjustment to the market demands via performing reconfigurations. In this problem the terminology is slightly different from the one applied in Chapter 3. In the short term, the available modules can be retooled to cope with the different parts to be assembled, which is referred to as a *changeover*. On a longer time horizon U, however, there is an opportunity to modify the set of available ones, this procedure is called *reconfiguration*. In a given cell, several products can be assembled. The cells are of multi-product type, which means production is performed in batches, and *setups* take place when switching from one product type to another. A setup involves the replacement of modules, and the adjustment of the technological parameters.

As for the external factors, market conditions and order stream are represented with a stochastic scenario tree, consisting of a set of nodes $\omega \in \Omega$ over a set of time periods U. Each node in the tree is associated with the forecast volume $f_{p\omega}$, the average lot size $l_{p\omega}$ and the assembly processes $j_{p\omega}$ of products $p \in P$. From production planning viewpoint, important assumption that information is available regarding the contractual batch sizes of products to be delivered periodically to customers. However, due to the uncertainties in the forecasts and other market conditions (e.g. set of product to be produced), an occurrence probability $\pi(\omega)$ is associated with each node. A path starting from the root node and ending in a leaf represents an evolution scenario with its occurrence probability. The objective of the problem is defined as it follows. Considering the overall time horizon U, a selection of a multi-cell system architecture is to be performed identifying the specific cell configurations z_{cu} that match the requirements realized in node ω corresponding to period $u \in U$, while minimizing the overall lifecycle costs over the horizon. This involves different questions (Figure 4.1), regarding e.g. the selected cell elements, applied layout, production and reconfiguration plans. These questions are addressed by the tools of the proposed assembly system design and management framework, as discussed throughout the next sections.

4.3 Assembly system design and management framework

The above specified design and management problem with the related sub-problems can be solved by applying the proposed framework, consisting of the four tools enlisted earlier. The tools utilize a common data repository, and act in an interactive way. This means that besides a general dataset is accessed by each of the tools, the results provided by the tools are utilized by other ones to refine the design and configuration determined in a preceding step, as well as the solutions are applied as feedbacks. The general data flow and architecture of the workflow is illustrated by Figure 4.2. The first tool is the *Assembly System Configuration Tool*, which is aimed at exploring the search space consisting of all possible system configurations, in which a system configuration refers to the generic design of multiple modular assembly cells. As the tool is capable of identifying all rough cell designs that match the global constraints, it enlists and visualizes them offering an option for the system designer to select the most promising ones. At this stage, the design is a draft configuration of a set of cells with the descriptions of cell building blocks, however, without a detailed configuration and task sequence. The latter problems are solved by the second tool called *Assembly Cell Configuration Tool*, applying a selected candidate rough cell configuration provided by the previous tool. The scope of the analysis is narrowed, as only a single cell is selected to refine its configuration, however, process level details are added at this stage including the arrangement of equipment in the cell into a layout, as well as selecting the proper task sequencing and evaluating the dynamic performances in an analytic way. This latter is then further evaluated from management point of view applying the *Production Planning and Simulation Tool*, taking into consideration the expected orders, inventory levels, production batch sizes and contractual delivery volumes. The performance indicators of the system under various production scenarios are predicted applying a DES model, thus considering the system with a greater detail. Finally, the *Reconfiguration Planning Tool* is applied to calculate the optimal evolution path of a cell along the scenario tree. The aim of this tool is to provide a robust design for the assembly cell, consisting of an initial configuration, and a sequence of reconfiguration steps, matching the system with the uncertain market evolution.

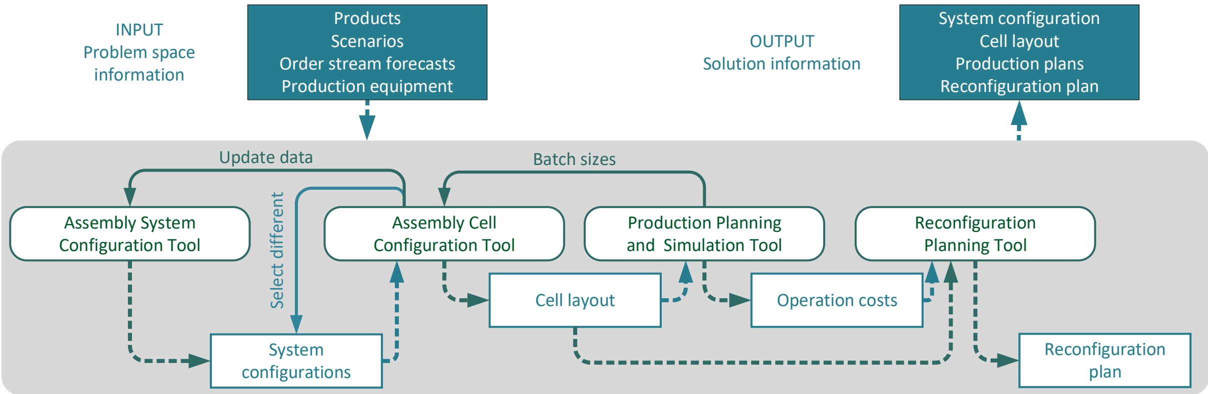


Figure 4.2. Design and management workflow for modular assembly cells.

4.4 Description of the applied tools

In this section the applied tools and models are presented, highlighting the *Production Planning and Simulation Tool* with the own results achieved within the collaborative development of the workflow. Before the detailed introduction of planning and simulation models, underlying models and calculations of the preceding tools are briefly introduced for the sake of completeness.

4.4.1 Assembly system and cell configuration tools

Assembly system configuration

The strength of the *Assembly System Configuration Tool* relies in its capability of exploring the whole solution space including all possible rough system configurations. It automatically generates the solutions, and also calculates the relevant KPIs. Besides, all generated solutions are displayed in various charts offering the system designers to select the proper configuration (to step forward with) intuitively. As detailed by Unglert et al. (2016), the tool applies a design synthesis methodology, to generate the possible cell configurations that match the constraints related to the market conditions, technological requirements and internal factors (e.g. the available shop-floor space). A core part of the synthesis is a knowledge base, populated with all design and system configuration related information and constraints. Based on the technical description of the set of applicable equipment (including also the purchasing costs) and the market demand, the minimum capacity requirement for each multi-cellular configuration is calculated. Then, capacity bounds are converted into bounds for the system design parameters, resulting in ranges of values for the number of equipment, defining e.g. the amount of modules r_{jp} to be applied. Having these ranges determined, an algorithm instantiates the possible solutions, defining the cells with corresponding technological equipment and assigned processes. The solutions can be displayed in various ways, providing the flexibility to compare alternative configurations, and check detailed information of the solutions, e.g. the KPIs, or the pieces of equipment. Applying this automated design synthesis, the time of creating the rough designs as well as comparing various alternatives can be significantly reduced. As a result, the designer can select a candidate (most promising) solution, to refine its configuration in a subsequent step.

Assembly cell configuration

The detailed cell configuration can be performed applying the *Assembly Cell Configuration Tool*, which is a composite tool consisting of multiple models that are directly linked with each other as introduced by Angius et al. (2016). The tool is capable of (i) handling different execution modalities, (ii) arranging the selected equipment on a layout and (iii) performing the dynamic performance evaluation analytically. Execution modalities (i) are different ways of performing a given assembly process, applying different pieces of equipment and/or modifying the task assignments. As a simple example for two different execution modalities, a spot welding process can be performed either by moving a part with a robot and applying a welding gun with a fix position, or, placing the part in a fixture and applying a welding gun installed on a robot. Various different ways of execution modalities exist to perform a given process, however, they require different equipment, and result in different performance and cost indicators. Therefore, their proper selection is of crucial importance towards the overall, detailed configuration of the assembly cell. The selection of candidate execution modalities results in the final set of equipment needs to be applied to configure the cell. This is performed by the layout planner algorithm (ii) that arranges the cell elements on the shop-floor, taking into account the general cell architecture with the skeleton and the reconfigurable modules. It also considers that technological modules can have auxiliary devices, or other tools to be placed. All in all, the layout planner model results in the final, detailed cell configuration that is capable of producing the predefined subset of products with a given task sequence and the corresponding processing and cycle times. This detailed configuration is evaluated analytically (iii) to determine dynamic performance indicators of the cell, supposing that estimated batch sizes $l_{p\omega}$ are available. The system dynamics is represented by a state-transition based model, assuming that every change of a state occurs according to Markovian distribution, and the underlying stochastic process is a *Continuous-time Markov chain.* The output of the model provide information about the buffer levels, utilizations and other cell parameters supposing dynamic changes. The most important result is a confirmation whether the configured cell meets the expectations regarding the target output rate.

Reconfiguration planning

As depicted by Figure 4.2, the final computation tool of the workflow is the *Reconfiguration Planning Tool* responsible for optimizing the cell configurations over time, with the objective of minimizing the overall lifecycle costs and considering various possible scenarios, as well as the co-evolution of products, processes and the system itself. The tool focuses on the configuration optimization of a single selected cell, adjusting its actual configuration in each period by applying reconfigurations, to be in balance with the market requirements. The aim is achieving robustness over the whole scenario tree, e.g. acquiring resources and equipment in advance (proactive approach), or waiting for the occurrence of a specific event to proceed with a proper reconfiguration (reactive approach). The reconfiguration planning, therefore, performs a stochastic optimization, considering all possible evolutions of a given cell over the horizon, represented by different paths along the scenarios tree from its root to a leaf. The reconfiguration strategy aims at minimizing an objective function considering the expected values of the incurred cost over all scenarios:

$$\text{minimize}\left(c^{\text{inv}}(z_{c0}) + c^{\text{opc}}(z_{c0}) + \sum_{\omega\in\Omega}\pi(\omega)\frac{c^{\text{inv}}(z_{c\omega}\mid z_{c0}) + c^{\text{opc}}(z_{c\omega}\mid z_{c0})}{(1+\delta)^{u_\omega}}\right) \tag{4.1}$$

Accordingly, the objective is composed of the expected investment c^{inv} and operation c^{opc} costs characterizing various cell configurations. The configurations are represented by $z_{cu} \in Z$, of which z_{c0} is the initial configuration in $u = 0$. As the scenario tree describes a stochastic market evolution, probabilities of scenarios occurrence $\pi(\omega)$ are considered, as well as a discount rate δ is applied to scale expected costs over time. The reconfiguration planning model is discussed in detail by Angius et al. (ibid.), highlighting that constraints include the calculation of costs, while respecting the limited amount of time available for production, and also the performance of the selected configuration with the applied execution modality.

As one can observe in (4.1), important element of the objective function, and the overall reconfiguration strategy is the future expected operation cost c^{opc} that also reflects implicitly the applied batch sizes of various products, and it is in the same order of magnitude with the investment costs c^{inv} in the long run. *Assembly Cell Configuration Tool* is capable of providing an estimation on the cell performance that one can expect if average contractual batch sizes $l_{p\omega}$ are considered, however, the applied production planning policy highly influence both values, thus it also affects the solution of the reconfiguration planning. Therefore, the *Production Planning and Simulation Tool* is applied before reconfiguration planning, in order to consider the most possible accurate values of the batch sizes and operation costs, and derive the cell configurations accordingly. The elements of the *Production Planning and Simulation Tool*, as well as the models behind are described in the following sections.

4.4.2 Production planning and simulation tool

Having the other tools of the workflow described, the *Production Planning and Simulation Tool* is responsible for calculating realistic production plans to predict the applied batch sizes considering production and logistics processes of multiple cells, utilizing a common resources pool. Besides, the executes the calculated plans with a simulation model, to predict the future expected operation costs that will probably incur when executing the plan, as these costs need to be respected when seeking for the cost-optimal reconfiguration strategy. The production planning tool of the workflow is aimed at predicting these costs characterizing a given cell configuration, based on the forecast order stream. The proposed method is able to handle the reconfigurable cells by module-specific constraints that prevent to hurt capacity limitations, thus resulting in feasible plans. Besides the planning, the second major part of the *Production Planning and Simulation Tool* is a novel discrete-event simulation model, implemented to execute the calculated plans by adding realistic random events (e.g. machine breakdowns) and representing the possible stochastic nature of production parameters. As the cells have fix components and also some changeable modules, a novel simulation modeling technique was applied, reflecting the real physical architecture and operation of cells with static model elements, and also with dynamically, runtime-created blocks. The main novelty and contribution of the *Production Planning* *and Simulation Tool* is twofold. On the one hand, a new mathematical model is applied with constraints that are able to handle the special characteristics of reconfigurable cells. On the other hand, the model usage is not restricted to plan the production, but it is rather applied to provide estimations on the future expected operation costs, refined also by the applied simulation model.

Production planning model for modular assembly cells

The planning tool calculates the production lot sizes, matching the contractual delivery volumes with a given system configuration. According to the scheme of Pochet and Wolsey (2006), the formulated model is classified as lot-sizing model with backlogging *(LS-C-B/M1)*, including additional system-specific constraints that are capable of representing the modular resources, taken by the cell from a common pool. The model can be seen as an alternative version of the production planning model for modular reconfigurable assembly systems (Section 3.4.2), however, new constraints are added to properly manage the setups, as their time is significantly longer than that of the lightweight modular systems. Due to the longer setups and significantly higher efforts put in the modules' replacement, a small bucket lot-sizing model was applied that involves the sequencing of the tasks, as only a single product type is assumed to produced within a planning time period.

The production environment is assumed to be completely known by taking into consideration the set of modular cells C defined by the previous tools. These cells are available for production, and capable of receiving a set of different modules J. The modules have a common resource pool with a specified amount r_j^{avail} of resources from each type. In the planning model, a discrete time horizon T is considered, consisting of periods $t \in T$ with equal length t^{w}. In the overall system with multiple cells, different products $p \in P$ are produced, each having a specific total machine cycle time t_p^{mach}, and total manual cycle time t_p^{man}, besides, product-independent setup time t_p^{set} is considered. The technological requirements of the assembly tasks of product p are represented by the amount of modules from type j that needs to be installed at the cell r_{jp}, and the technological constraints are summarized in a compatibility matrix a_{pc}, composed of elements that equals to 1 if product p can be assembled in cell c, and 0 otherwise. In the specified planning model, contractual delivery volumes d_{pt} are considered to plan the production. Decision variables determine the production lots x_{ptc}, specifying the volume of product p assembled in cell c in period t. Assembled products can be either delivered to the customer (s_{pt}) or kept in the inventory (i_{pt}), however, the latter is associated with certain costs. Besides the assignment of production lots and machine capacities, an important decision is to determine the headcount of operators h_{ct} working at cell c in period t.

The production planning problem is formulated as a mixed-integer linear programming model by (4.2)-(4.15). The objective function of the production planning is the sum of backlog, inventory holding and operator costs that should be minimized (4.2). The first constraint represents the module requirements of products, in order to avoid the insufficient amount of resources as they are shared among the cells by the reconfigurations (4.3). Constraints (4.4) and (4.5) respectively state that manual and machine capacities cannot be exceeded. In case $t_p^{\mathrm{man}} > t_p^{\mathrm{mach}}$ (e.g. if several parts need to be handled by the operators), the production takt of the cell is limited by the human capacities, therefore, it is important to allocate enough workforce to maintain the smoothness of production. In case $t_p^{\mathrm{man}} < t_p^{\mathrm{mach}}$, the production takt of the cell equals to the machine cycle time, hence, a single operator is enough to perform the manual processes.

Inequality (4.6) states that customer requested volumes needs to be delivered. In case there are not enough products in the inventory, backlogs will occur. Constraints (4.7)-(4.13) represent the setup requirements when the production of a new batch is to be started in a given cell, expressed by the binary indicator variable g_{ptc}. Additional indicator variable is y_{ptc}, expressing if a given product p is assembled in cell c in period t. This variable is also used in (4.10) to constrain the assignment of batches to cells. Important assumption is that a certain cell c can have a setup to a single product p only in a period t. In (4.8), the coefficient Λ is required to properly calculate the reconfigurations, its lower bound is $\Lambda > t^{\mathrm{w}}/(\max_{p \in P} t_p^{\mathrm{mach}})$. The balance equation (4.14) is responsible for linking the subsequent time periods with each other through the delivery, inventory and production volumes.

$$\text{minimize}$$

$$\sum_{p \in P} \sum_{t \in T} \left(c^{\mathrm{bl}} b_{pt} + c^{\mathrm{stock}} i_{pt} \right) + \sum_{c \in C} \sum_{t \in T} c^{\mathrm{opr}} h_{ct} \tag{4.2}$$

$$\text{subject to}$$

$$\sum_{c \in C} \sum_{p \in T} r_{jp} y_{ptc} \leq r_j^{\mathrm{avail}} \qquad \forall\, t \in T,\ j \in J \tag{4.3}$$

$$\sum_{p \in P} \left(t_p^{\mathrm{man}} x_{ptc} + t_p^{\mathrm{set}} g_{ptc} \right) \leq t^{\mathrm{w}} h_{ct} \qquad \forall\, c \in C,\ t \in T \tag{4.4}$$

$$\sum_{p \in P} \left(t_p^{\mathrm{mach}} x_{ptc} + t_p^{\mathrm{set}} g_{ptc} \right) \leq t^{\mathrm{w}} \qquad \forall\, c \in C,\ t \in T \tag{4.5}$$

$$s_{pt} \geq d_{pt} \qquad \forall\, p \in P,\ t \in T \tag{4.6}$$

$$\sum_{p \in P} y_{ptc} \leq 1 \qquad \forall\, c \in C,\ t \in T \tag{4.7}$$

$$x_{ptc} \leq \Lambda y_{ptc} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.8}$$

$$x_{ptc} \geq y_{ptc} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.9}$$

$$y_{ptc} \leq a_{pc} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.10}$$

$$g_{ptc} \leq y_{ptc} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.11}$$

$$g_{ptc} \geq y_{ptc} - y_{p,t-1,c} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.12}$$

$$g_{ptc} + \sum_{\substack{q \in P \\ q \neq p}} \left(y_{qtc} - r_{qtc} \right) \leq 1 - y_{p,t-1,c} \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.13}$$

$$i_{pt} - b_{pt} = i_{p,t-1} - b_{p,t-1} - s_{pt} + \sum_{c \in C} x_{ptc} \qquad \forall\, p \in P,\ t \in T \tag{4.14}$$

$$g_{ptc}, y_{ptc} \in \{0,1\} \qquad x_{ptc}, s_{pt}, i_{pt}, b_{pt} \in \mathbb{Z}^+ \qquad \forall\, c \in C,\ t \in T,\ p \in P \tag{4.15}$$

The rationale of applying the above production planning model in the design method of reconfigurable cells is twofold: on the one hand, it supports the designers to estimate the cell's future behavior, and on the other hand, it can be applied to proactively determine the future expected batch sizes and operation costs that are both relevant in the proposed methodology. Important to highlight that the *Assembly Cell Configuration Tool* (the previous element of the workflow) could calculate only with the idealistic, static batch sizes, and evaluated the systems performance accordingly. The calculated realistic batch sizes derived from the customer order stream are fed back towards the *Assembly Cell Configuration Tool* to re-evaluate the system performance, and validate the feasibility of a system configuration (Figure 4.2). Moreover, the operation costs can be refined based on the production planning model's solution. Precise information about these costs is important input of the *Reconfiguration Planning Tool*, as discussed later.

Generic simulation model for modular assembly cells

This refined information can be obtained by running the simulation model of the system, capable of executing the previously calculated plan, while adding even more details compared by the deterministic planning model. The simulation model represents the possible stochasticity of parameters, and also the random events that might affect the system's behavior. This leads to another dynamic evaluation of the system, which differs from the previous one performed by the *Assembly Cell Configuration Tool* applying analytical models. The simulation-based dynamic performance evaluation is aimed at adding novel aspects to the analysis, considering not the single cell only, but a system-wide evaluation of the production environment with the linked processes of the value chain. Therefore, the evaluation is based on a simulation model including multiple reconfigurable cells, and also the complementary processes. First main input of the simulation is the description of assembly processes that specify the processing times, routings in the cell as well as the manual processes. Other important input of the analysis is a given production plan calculated in the preceding step. Having the plan specified in the analysis, resource sharing and, therefore, the inter-cellular processes can be analyzed that was not possible in the preceding steps of the workflow. The purpose of executing a dynamic analysis is to evaluate the cell's performance, whether it can provide the desired output rate or not, and besides, to predict the operation costs that will probably incur when executing a production plan. In this way, feedback information to both the preceding cell configuration steps and the production planning is provided, regarding the quality of the calculated solutions.

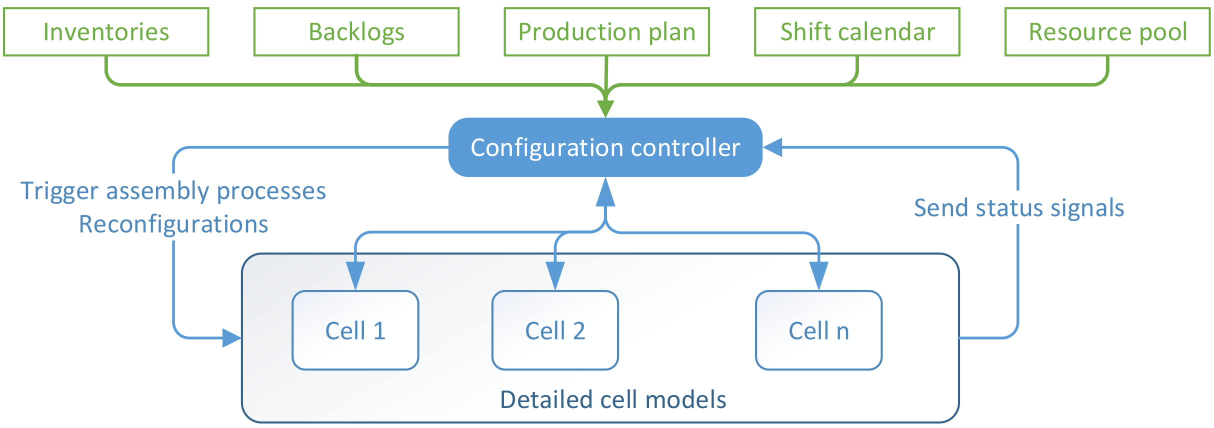


Figure 4.3. Scheme of the simulation model defined for modular reconfigurable assembly cells.

As stated, the evaluation needs to focus on multiple reconfigurable cells that share the resources, instead of analyzing a single cell only. Besides the general dynamics of production processes, material handling, assembly processes, in- and outbound logistics, reconfiguration of the cells introduce new challenges in the analysis and especially in the modeling process. In order to tackle them, a novel simulation model architecture is proposed, defined specifically for modular reconfigurable assembly cells. Representing the real, physical structure of cells composed of a static skeleton and changeable modules, the simulation model has also two main elements: a static configuration controller and continuously changing detailed cell models (Figure 4.3). The core element of the model is a cell controller, responsible for representing all processes and objects of the production system except the changeable modules. Static components of the model are elements of the cell skeleton with the inbound logistics objects, buffers, transportation system (if exist) and also the objects responsible for managing the shift calendar of the operators and process the production plan that determine the size and release time of production lots. Moreover, the configuration controller manages the inventories by controlling the deliveries and calculating the backlogs.

Besides the static element of the model, dynamically changing detailed cell models are performing in-depth simulation of assembly processes. These models are built-up automatically when setups take place. Setup events are triggered by the configuration controller, when assembly of a previous lot is finished and a new one is to be started. During a setup, the necessary modules are installed on the cell by moving them to the proper position in the model and adjusting the proper processing times. The prerequisite of a setup is that all necessary modules need to be available (they can be used by other cells), otherwise the procedure is delayed until each module becomes free. In the detailed cell models, the intra-cell material flow is represented in-detail with the predefined processing steps (execution modalities, processing times etc.) and routing of the parts. The connection among the configuration controller and the cell models is established by event triggers in both directions: the parts are assembled according to the production plan managed by the controller. If a new part is produced, a trigger event is sent to the detailed cell model that executes a detailed simulation of assembly processes. After a part is completed, a confirmation signal is sent back to the controller to convey the part in the warehouse or to other processes. A more detailed description of the simulation model and its interfaces with the *Production Planning and Simulation Tool* and the reconfigurable cell controller are provided by Gyulai et al. (2016).

4.4.3 Implementation in the Simulation and Navigation Cockpit

The developed modules have been integrated into a common software platform called Simulation and Navigation Cockpit[3]. In general, the cockpit can be characterized as a multi-purpose, service-oriented software framework, offering users to define and run specific scenarios and experiments to solve robust design, planning and control tasks. The core elements of the cockpit are services that are connected with each other to set-up different workflows, and able to reach a predefined set of data stored in the central database, moreover, they can access the predefined set of calculation tools, e.g. discrete-event simulation, mathematical optimization of computation design synthesis. Each service and part of the cockpit can be controlled by the user via a graphical, web-based interface supporting the management of different user roles as well. In this way, workflows can be defined in a collaborative way, which means that the different objectives of the users can be considered in a single workflow (Figure 4.4). To achieve tne integration of individual modules, all of them operate on the same database, which makes possible to use the modules sequentially or in an independent way. The central database ensures the interoperability

[3]Developed within the European Seventh Framework Programme project Shock-robust Design of Plants and their Supply Chain Networks (RobustPlaNet), under grant agreement No. 609087

of modules by means of the *Core Manufacturing Simulation Data* (*CMSD*) standard model (Lee et al., 2011). Moreover, workflow-specific interfaces make possible the transfer of data between the modules.

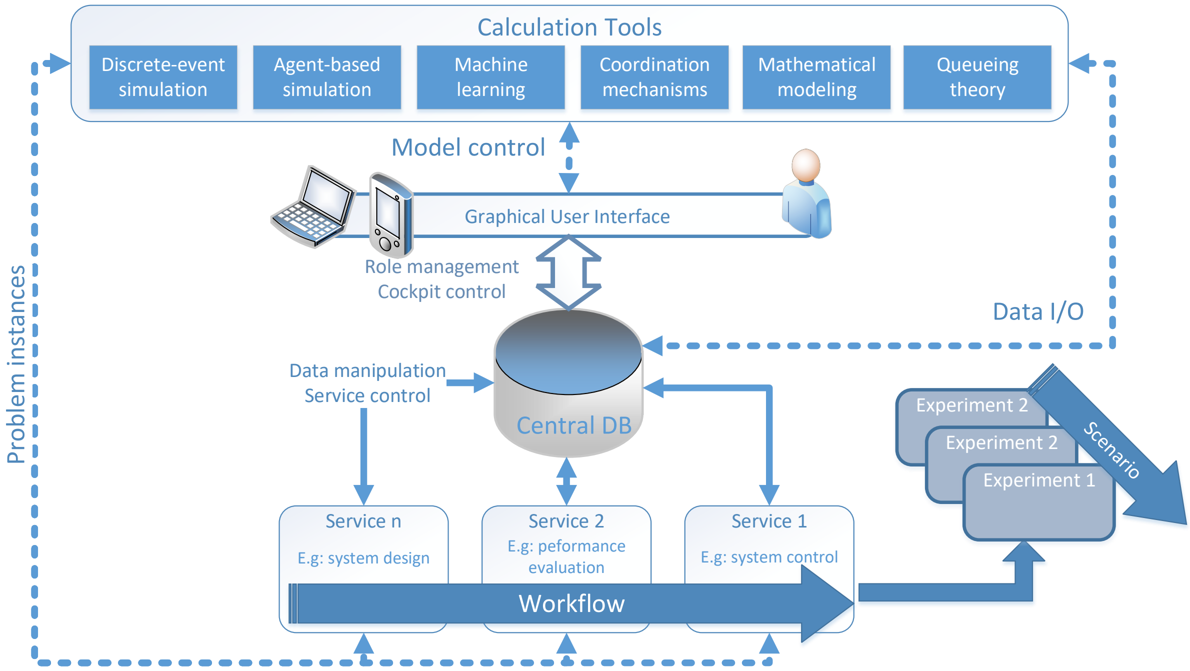


Figure 4.4. General architecture of the Simulation and Navigation Cockpit.

Typical use is the execution of tools sequentially, according the workflow in Figure 4.2. However, information feedback between the tools can be also exploited. It might happen that a solution turns out to be infeasible at a certain stage and the root solution needs to be refined by the tool working upstream in the workflow. In the proposed methodology, three main feedback loops are defined to exchange information among the modules. After identifying a favorable multi-cell system configuration with the *Assembly System Configuration Tool*, an individual cell is considered in detail using the *Assembly Cell Configuration Tool*. In this step, it is important to evaluate whether the selected equipment can be arranged into a layout that is still compliant with the assumptions used in the *Assembly System Configuration Tool* with regards to cycle times and available capacity considering the associated performance evaluated. In case the production rate does not reach the target value, the bottleneck operations and the corresponding modules are identified. Based on this information, another solution from the *Assembly System Configuration Tool* is used as input for the *Assembly Cell Configuration Tool*; or input data for the *Assembly System Configuration Tool* is redefined to synthesize and valuate new system configurations. The second main feedback loop is implemented to backlink the results of the *Production Planning and Simulation Tool* to the *Assembly Cell Configuration Tool*. In this case, the information added on the lower level, mostly refers to batch sizes, coming from the production planning. The average batch sizes can be different from what initially defined; while fixed batch sizes are assumed when calculating the layout configuration and the corresponding process sequence, the planning module can consider variable batch sizes in order to match the requirements of the customers. In this case, the evaluation of the performance is operated again considering the new average batch sizes. A third feedback refers to operation costs calculated by the *Production Planning* *and Simulation Tool*. Grounding on a simulation approach, operation costs can be calculated precisely considering the detailed logistics constraints, providing feedbacks to the *Reconfiguration Planning Tool* that might change the reconfiguration sequence along the horizon. Hence, the optimal solution can change and a new optimal sequence of reconfigurations must be identified.

4.5 Industrial application case

The overall system design and management framework, as well as the individual tools were applied to an automotive case. The results of the case study are detailed in the following sections, highlighting the solutions provided by the *Production Planning and Simulation Tool*, and its application as an integrated part of the workflow.

4.5.1 Description of the application case

In the application case, a *Tier-1* automotive supplier is selected, producing car body parts for OEMs. The external environment is characterized by fragmented orders, resulted by the ever changing product portfolio, and also by frequent changes in joining technologies that the company should follow according to the specifications created by the OEMs. Although total yearly volumes are relatively constant over time, new products are continuously added to the portfolio, therefore, the demands correspond to smaller batches. The company has limited shop-floor space, thus this high-mix-low-volume production requires efficient variety management strategy to keep the competitiveness and internal efficiency. Moreover, the market environment is uncertain, increasing the problem complexity.

In the case study, four different products ($P1 - P4$) are selected, for which a modular cell is to be configured and managed over a time horizon of three periods ($u \in U$), with equal lengths of three months (480 working hours). Each product has its own assembly specification with the corresponding technologies that need to be applied. In the analysis, only joining technologies are considered, of which products require nut pressing, resistance spot welding, adhesive joining and riveting. These technologies are performed by the combination of fixed equipment (skeleton) and a set of modular devices $j \in J$. The equipment dimensions are known (only 2D dimensions are considered), as well as the investment costs of the devices, ranging between €10.000-€120.000. The hourly labor costs are known (50€/h), and the total time consumption of performing major changes in the cell configuration (reconfiguration) is two working weeks. The results of assembly system configuration are presented as follows.

4.5.2 Assembly cell configuration results

First, multiple rough cell designs were created by the *Assembly System Configuration Tool*, relying on the available information about the expected market situations. By defining input data about the products and corresponding processes, candidate cell configurations were created that match the expected output rate. These configurations are built up of the equipment that was stored in the repository. For the same scenario (product mix and order volumes), multiple different cell alternatives were defined, of which designers can select the most promising one(s) for further, more detailed analysis. The created solutions differed in the total occupied area, total initial investment costs, and also in other predicted cost factors, e.g. the operation, logistics and storage costs.

The *Assembly Cell Configuration Tool* was then applied to generate a cell layout by arranging the set of equipment selected in the previous step. Besides, the set of possible execution modalities was identified, defining task sequences and resource-task assignments. Two different layouts were generated, of which the one with shorter total cycle time was selected to be the applied. Based on the investment costs, the operational costs (calculated as discussed in the following section) and the stochastic market environment represented by the scenario tree, the reconfiguration strategy could be determined by the *Reconfiguration Planning Tool*. Along the time horizon U, expected production volumes, as well as the set of products to be produced in the cell were changing. Therefore, the cell reconfiguration strategy was defined by stochastic optimization, identifying the pieces of equipment that need to be added (or removed) to the cell configuration in a given period u, within a reconfiguration. As the *Reconfiguration Planning Tool* planning tool strongly relies on the data about operation costs, prediction and refinement —considering a system-wide production planning— of these parameters were performed with the *Production Planning and Simulation Tool*.

4.5.3 Production planning and simulation results

Applying the *Production Planning and Simulation Tool*, one can analyze the future expected operation costs and production batch sizes, based on the contractual delivery volumes known already in the early design stage. Relying on the defined application case, inputs of the tool are system configurations for the subsequent time periods, as well as delivery volumes agreed with the customers. The main purpose of the planning is to refine estimation on the batch sizes: whereas previous tools of the workflow considered average batch sizes, in this case, they are calculated by matching order stream with a detailed system structure. Executing these plans in the discrete-event simulation model of the system, realistic operation costs can be calculated that consider additional information compared to the previous module, as inventory, personnel and also backlog costs can be determined in this way. The refined operation costs are meaningful feedback information that can be applied by the *Reconfiguration Planning Tool* to select the cost-optimal reconfiguration strategy. Besides, batch sizes can be utilized by the *Assembly Cell Configuration Tool* to evaluate and/or refine the cell configuration.

In the experiments, four different scenarios were analyzed with the planning and simulation models. In the first scenario *(contractual)*, the contractual delivery volumes and frequency were applied (represented by variables d_{pt}), evaluating the solutions calculated by the *Assembly Cell Configuration Tool* considering ideal order stream. In the other three scenarios *(Sc #1-3)*, delivery frequencies were increased by splitting the total volumes in smaller parts. In these scenarios, the total volumes were the same, while delivery frequency was increased by $10-20-30\%$ subsequently. This resulted in smaller production batch sizes, more changeovers and thus higher operation costs, which might occur in real life. All experimental results are reported in Table 4.1. The results show that even in the contractual case, operation costs are higher than those considered by the previous modules. This refined information can be applied by the *Reconfiguration Planning Tool*, if one assumes that contractual volumes will not change in the future. A more conservative solution is applying the operation costs resulted by *(Sc #1-3)* scenarios, where smaller batch sizes and higher costs are resulted.

Based on the above results, a robust cell reconfiguration strategy could be identified that minimizes the overall lifecycle costs of the cell, including investment, operation and reconfigura-

Period	KPI	Ideal	Contractual	Sc #1	Sc #2	Sc #3
u_0	c^{opc} [€]	10 863	13 714	14 030	16 028	17 184
	Batch_P1	40	124	42	42	33
	Batch P2	0	0	0	0	0
	Batch P3	30	50	40	30	30
	Batch P4	0	0	0	0	0
u_1	c^{opc} [€]	11 478	15 456	16 627	18 663	20 677
	Batch_P1	0	0	0	0	0
	Batch P2	0	0	0	0	0
	Batch P3	30	53	53	40	40
	Batch P4	35	42	33	33	25
u_2	c^{opc} [€]	14 637	17 779	19 406	22 452	21 772
	Batch_P1	35	127	124	124	124
	Batch P2	40	47	40	33	27
	Batch P3	35	50	50	33	33
	Batch P4	35	42	33	33	33

Table 4.1. Feedback on the resulted operation costs and batch sizes provided by the *Production Planning and Simulation Tool*. The *Ideal* includes the costs and batch sizes considered by the previous tools, whereas *Contractual* refines these costs. Scenarios Sc #1-3 assume that contractual delivery volume might change in the future resulting in more frequent deliveries.

tion costs. As discussed by Colledani et al. (2016), this robust reconfiguration strategy resulted in better solution than the so-called single path optimum that takes into account a single scenario of the tree, and looks for the best configuration in each time period. The robust solution, however, considers all possible scenarios with their probabilities, and determines the reconfiguration strategy accordingly. The solution (cell configuration) selected for the case study is illustrated in Figure 4.5. This cell configuration results in the lowest overall lifecycle costs along the horizon, while meeting the requirements of all possible market scenarios without major changes in its configuration (reconfiguration), but it is enough to exchange the assembly modules when a setup takes place.

Important elements of the workflow are the feedback loops, implemented to refine a given configuration if requested after an evaluation with a subsequent tool, applying more detailed input data. Focusing on production planning, the results are applied to refine the system configuration with the *Assembly Cell Configuration Tool* if batch sizes differ from the previously considered ones. As reported in Table 4.1, the need to consider all details and constraints at the planning level could entail different feasible lot sizes compared to those used in the *Reconfiguration Planning Tool*. This could affect operation costs, moreover, might have impact also on the cell's performance, if the actual lot sizes are smaller. This information can be exploited in the overall approach in two ways:

- using the new estimated operational costs to identify a possible new optimal solution through the *Reconfiguration Planning Tool*;
- using the new estimated batch sizes to search for alternative configurations using *Reconfiguration Planning Tool*.

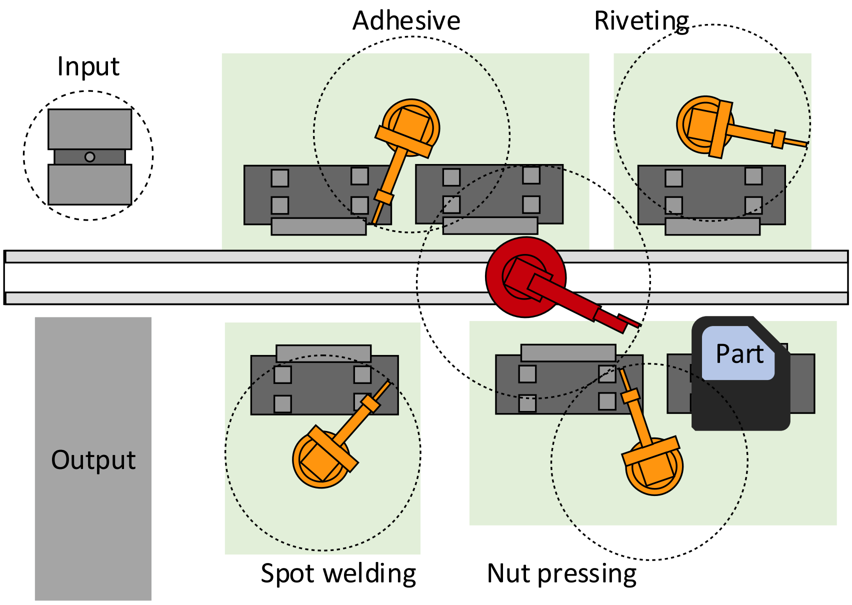


Figure 4.5. Robust cellular layout of a modular reconfigurable assembly cell. This solution can face the production requirements of all the scenarios $\omega \in \Omega$.

The first option can be implemented by simply substituting the new operational cost for each period, obtaining a refined discounted total cost. If significant differences might be observed among the batch sizes, it is suggested to recall the *Assembly Cell Configuration Tool* to seek for alternative configurations to be applied in the reconfiguration planning as well.

The complexity of the problem and the corresponding calculation times are summarized as they follow. The production planning and DES models were implemented in FICO® Xpress and Siemens Tecnomatix® Plant Simulation, respectively (FICO, 2017; Siemens, 2016). The planning model addresses the whole system, potentially including multiple cells (including the one under evaluation) sharing a common pool of hardware modules. The complexity of the analyzed problem is characterized by the average values of $|P| = 20$ products (including the four selected products), $|C| = 5$, $|J| = 7$, and the contractual delivery frequency of products was $t = [4, 12]$ on a $|T| = 60$ length horizon, covering a single time bucket $u \in U$ of the reconfiguration planning model. This resulted in a running time of 44 seconds in average with *Xpress'* default MIP solver, until an optimality gap of at most 5% was achieved.

4.6 Summary of Chapter 4

In Chapter 4, a new design and management method and the corresponding framework were introduced that are capable of providing robust designs for modular, reconfigurable assembly cells. The method is represented as a workflow consisting of four different tools that were chained together by utilizing each others' results. The initial step is the generation of rough cell designs, considering all possible alternative solutions of the search space that satisfy the market and production constraints. Then, user-selected candidate solutions are refined by performing the task sequencing, layout planning, and also an analytical performance analysis. As the cells are configured so as to match the market changes, a reconfiguration planning module is applied to optimize the system configuration along the horizon, implementing the co-evolution of products, processes and system structure.

In order to minimize the lifecycle costs of a cell, operation costs need to be strictly considered, as in the long run, they are in the same order of magnitude with the investment costs. Therefore, a system-wide production planning is performed that balances the internal capacities with the external orders, considering that cells apply dockable technological modules, taken from a common resource pool. The production planning relies on contractual delivery volumes that are known already in the design stage of the cells, and a plan provides information about the future expected batch sizes, moreover, it is executed in simulation environment to predict the operation costs. As they rely on more detailed information —compared to the ones considered in the preceding calculations—, these results on the costs and batches are utilized in reconfiguration planning, as well as in the system configuration tools. The workflow was defined and elaborated within a collaborative research together with academic partners, therefore, emphasis in the section was put on the *Production Planning and Simulation Tool*, which is presented as the own scientific result of the collaboration. Similarly to other tools of the workflow, the main contribution of the *Production Planning and Simulation Tool* is its capability of coping with the peculiar modular and reconfigurable cell architecture described in Section 4.2. The system-specific constraints of the mathematical model control the resource consumption by combining the use of fixed (C) and exchangeable (J) resources in the production plan. Moreover, the applied DES model also applies a novel model building procedure and simulation approach to represent the system operation in a realistic way, with the static-built central model controller and the dynamically created technological blocks.

Chapter 5

Robust production planning

Having solutions proposed for the capacity management of modular assembly systems, from this section, the focus is shifted to the robustness of calculated production and capacity plans, in order to cope with the variability of planning parameters. Whereas in the previous chapters the emphasis was put on the capacity scalability by adding and removing modules to the assembly system, in the following, the capacity of lines will be adjusted by the rate and allocation of human workforce. A new, proactive method is proposed that utilizes the combination of corporate and shop-floor data to calculate production plans that are robust against the variability of manual processing times, and reject rates of products that lead to uncertain extra capacity requirements.

5.1 Robust planning for assembly systems

As introduced in Section 2.5, production planning of assembly systems is a challenging task, as the often fluctuating order volumes require flexible solutions. Moreover, the calculated plans need to be robust against the process-level disturbances and stochastic nature of some parameters like manual processing times or rework rates of products, both resulting in extra human capacity requirements. The aforementioned effects are characteristics of manual assembly lines, and neither conventional ERP, nor state-of-the-art APS systems are able to handle correctly these factors, as their prediction is a complex and challenging task due to the influence of underlying production processes. In this chapter, a simulation-based optimization method is proposed that utilizes lower level shop-floor data to calculate robust production plans for flexible, manual final assembly lines of a multi-stage production system. In order to minimize the idle times when executing the plans, the capacity control —specifying the proper operator-task assignments— is also determined. The analyzed multi-stage system is operated with a pull strategy, which means that the production at final assembly lines generates demands for the preceding stages providing the assembled components. In order to guarantee the feasibility of plans calculated for the final assembly lines, a decomposition approach is proposed to optimize the production plan of preceding stages. In this way, robust production can be ensured resulting in reduced losses and overall production costs, even though the system is exposed to changes and disturbances.

5.2 Problem statement

The analyzed production system is composed of multiple stages: the final products are assembled on flexible, manual flow lines, designed for producing different product variants in batches, while the main components are machined in a preceding machinery segment. Multi-stage production systems require special planning approaches to balance and coordinate production along the entire process chain. In the analyzed case, precise planning is important to minimize the changeovers required to setup the line from one product variant to another, besides, capacity control is responsible for allocating the proper amount of human workforce to the processes, to keep the customer due dates without lateness. The above characteristics result in a special version of the MLCLSP, in which a complementary problem of the human capacity control also needs to be solved, meanwhile, the solution of this subproblem is utilized when planning the production.

The primary focus is on the production planning of assembly lines, seeking cost-optimal plans that determine lot sizes, release dates and capacity requirements, too. In order to handle the changes and disturbances in a robust way, the proposed planning method is combined with a lower level capacity control, specifying the work hours and when and to which workstations human resources are allocated (Rossi and Lödding, 2012). While the objective of planning is to decrease costs by eliminating the unnecessary changeovers and reducing stock levels, capacity control is responsible for balancing the workload of operators and eliminating idle times. The overall objective is to calculate near-optimal, robust plans for the final assembly lines, pulling the production of previous stages. As the customer service level of the company is mostly influenced by the completion of final-products, the resulted plans need to be robust against the assembly-related changes and disturbances (e.g. machine breakdowns or process time deviations) that have negative impact on the service level. In order to maintain this performance indicator on a desired level, a decomposition approach is proposed, splitting the multi-stage production planning problem in two subproblems: the combined production planning and capacity control of the final assembly lines, and the production planning of the preceding stages. In order to meet the quantity and due date requirements of customers, the problem of assembly lines is solved first, as the pull strategy directly generates demands and thus constraints in the production planning problem of preceding, so-called pre-inventory stages. In this way, the integrity of production plans along the entire process chain can be guaranteed.

5.2.1 Characteristics of the considered production environment

In order to define the planning problem precisely, the main characteristics of the production system are introduced first as they follow. The production environment under study is a generic multi-stage system operated by pull production strategy, and consisting of automated as well as manual process steps. The first stage is a machinery, producing the main components of products, assembled later in the final assembly stage. Between the assembly lines and the machinery, an in-process inventory is found, splitting the process chain into two main parts: the pre-inventory processes and the final assembly (Figure 5.1).

Pre-inventory processes

In the machinery, components are manufactured on flexible resources, and a single machine is enough to complete all machining processes of a given workpiece. Although machines are automated, material handling and setup processes require human labor, provided by assigning the operators to machines with different control modes. These control modes determine the operator-machine assignments, and they are adjusted according to production volumes. The machined

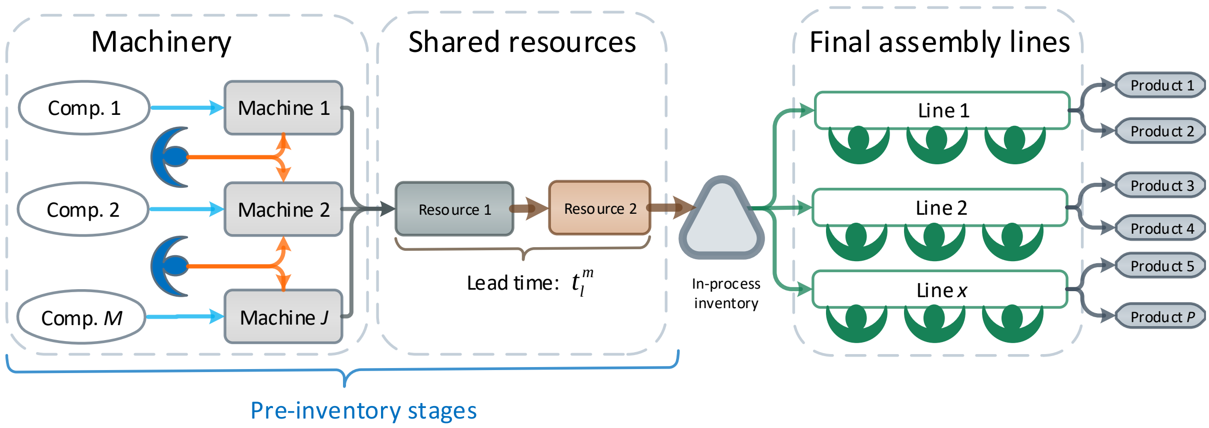


Figure 5.1. Scheme of the analyzed process chain.

parts are transferred to shared resources, where processing times are workload independent but product-specific, therefore, this stage is characterized with the lead time of a single product from the machinery to the in-process inventory. Holding this inventory is necessary to balance economic production lot sizes of the machinery and assembly segments, as in general, bigger lots are preferred in the machinery due to the significantly longer setups than those of the assembly lines.

Final assembly lines

The final assembly lines' segment is the last stage of the process chain, where final products are assembled from the previously machined main components, and additional parts provided by external suppliers. The products are assembled on flexible flow lines that are capable of producing a set of different product types in separate batches. Similarly to the machinery, setups take place when changing from one product type to another, however, these setups are significantly shorter than those of the machinery. The lines have a generic structure, consisting of manually operated workstations, an automated test machine and a manual rework station. Each product has to pass a functional test, and products failing the test are transferred to the rework station for correction, after which they are retested. The ratio of total retested parts and total assembled parts is expressed by the reject rate that is mainly product type dependent, and means a challenging stochastic factor when balancing the workload and planning the production. The lines' output rate can be adjusted by the allocated human workforce, therefore, it is a crucial point to find the right balance between human and machine capacities to assemble the target volumes and keep the workload of operators on a desired level.

5.2.2 Specification of the combined planning and control problem

Component supply planning

The pre-inventory processes are considered as suppliers of the main components required by the assembly stage to finalize the products. In the analyzed case, each product type requires one main part produced in the pre-inventory stage, thus in the followings the term *component (or part)* will refer to a single main part of a given product type. The whole system is operated with a pull strategy, thus customer orders for final products bound the production of preceding stages. In the planning problem, a discrete time horizon is considered, consisting of a set of micro time periods Π, each period $\pi \in \Pi$ having the same length t^{π}. Compared to the planning model of assembly lines, the resolution of pre-inventory planning model is higher, as $t^{\pi} < t^{\mathrm{w}}$. This higher resolution $t^{\pi} = \frac{t^{\mathrm{w}}}{\rho}$ enables to simplify the lead times t^{l}_{m} to be given in micro periods, without significantly reducing the accuracy of the plans. Moreover, this formulation of lead times in assembly production planning can preserve the option of decomposing the problem into a set of single-item lot-sizing models (Pochet and Wolsey, 2006). The volume demands determined by the final assembly is available on the whole planning horizon $|\Pi|$. The main questions are the production lot sizes $z_{m\pi j}$, specifying the volume of component m machined in time π on machine j. Besides, the corresponding control modes $r_{oj\pi}$ has to be determined that give the assignment of operator o and machine j in time π. The objective is to minimize the overall production costs, consisting of operator and inventory costs. In the problem of component supply planning, not only the machinery segment but also shared resources are considered.

Final assembly planning and control

As the final assembly lines have a common generic structure, the emerging production planning and capacity control problem is similar to the one specified for the pre-inventory processes (Section 5.2.2). In this case, customer orders directly influence the production plan, as they refer to the end products. Therefore, the order volumes of different product variants are available on a certain horizon, split up into a set of production periods T. In case of the final assembly lines, the planner has to decide about the production lot sizes of different product variants x_{nt}, and the corresponding shift plan that specifies the headcount of operators h_t in each shift t. Each order $n \in N$ is characterized by its volume q_n and completion due date t^{d}_{n}. Make-to-stock option is available in each shift, therefore, in case of capacity shortage, orders can be fulfilled from stocks, however, holding inventory, as well as order completion after the due date (backlogging) are penalized with extra deviation costs c_{nt} expressed by (3.1). The planning objective is to provide a near-to-optimal production plan that is robust against the stochastic capacity requirements, results in minimal production costs and increased utilization of resources (machines and human operators).

The capacity control of a final assembly line specifies the proper assignment of operators to assembly tasks, in order to balance their workload and decrease the idle times caused by the product-dependent bottleneck and reject rate. In this sub-problem, the objective is to determine the assignment policies for each product type, and each possible operator headcounts (that can be applied to assemble a given product type). It means that the number of operators can be changed periodically to adjust the production rates. However, several production lots are released in one shift requiring different operator-task assignments, while the headcount of operators cannot be changed. In industrial practice, this problem is solved by defining standard work instructions based on the norm times, however, this approach often tends to be inefficient as the norm times are considered to be deterministic, whereas they have certain deviation in the real life.

5.3 Production planning method with decomposition

In order to solve the complex multi-stage planning and control problem described above, a decomposition approach is proposed. In this way, the complexity of the multi-stage lot-sizing problem can be reduced to feasible single-stage subproblems, while the coherence of the final solution is ensured by linking the models via interdependent constraints. As the customer orders need to be managed in the production planning model of final assembly lines that pull the production of preceding stages, the whole problem can be decomposed at the inventory, which is responsible for balancing the material flow between assembly and machinery. Consequently, the resulted subproblems can be described with two planning models: the production planning (and capacity control) models of assembly lines, and pre-inventory system.

First, the planning problem of the assembly lines needs to be solved, since the resulted plan generates demands for the preceding stages. In case the process chain is virtually cut at the inventory, the schedule of assembly lines specifies the volume of main components, needs to be available in the inventory to assemble the product in time. This inventory level can be applied as a constraint in the production planning model of pre-inventory stages. Having the lot sizes determined in the above described way, the corresponding human workforce requirements also needs to be specified. In the machinery, it gives the operator-machine assignments, while in the assembly segment, it means the in-process capacity control, more specifically the headcount of operators and operator-task assignments. In the machinery, operators perform material handling only, which means changing the products in fixtures. This can be done in parallel with machining of other parts, therefore, a single operator is usually assigned to more machines at the same time. In the assembly segment, operators perform the processes themselves, therefore, it is essential to assign them a proper workload in order to avoid overload and thus late execution of the plan. Moreover, underestimation of the workload results in idle times and extra costs, which is also avoidable when calculating the capacity control. Therefore, in the machinery, shift planning and lot-sizing are done together applying a single model, whereas in the assembly case, capacity control is decoupled from the production planning model and only the necessary headcount is calculated together with the production plan. The above defined planning workflow is depicted by Figure 5.2.

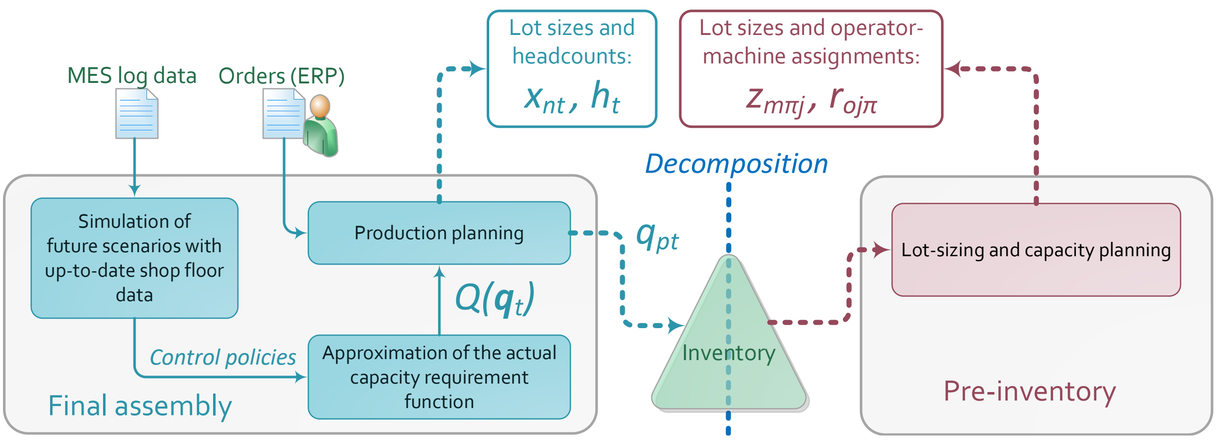


Figure 5.2. Robust production planning and control workflow.

5.4 Robust planning method for flexible final assembly lines

5.4.1 Description of the applied simulation models

The robust planning method of final assembly lines relies on simulation models, which are used for multiple purposes: on the one hand, capacity control of the lines are derived from simulation results, on the other hand, the models are capable of providing realistic data to build reliable capacity prediction models upon. The simulation model of the lines are built by applying a common data representation, utilizing the generic structure of the lines. Static elements in the simulation model are only the objects representing the lines' structure (workstations, layout), and routings of products. The essence of the simulation model is a data interface, ensuring that each relevant production parameter is updated before the experiments gather actual data from the MES. In this way, processing and testing times, reject rates, and machine availability are given as stochastic values by obtaining the parameters of distribution functions from the latest MES log data (Pfeiffer et al., 2017). Accordingly, the tight link between the simulation model and the physical system can be always maintained, resulting in reliable results without any direct user interaction (Monostori et al., 2010).

5.4.2 Simulation-based capacity control of flexible assembly lines

First step of the proposed robust planning method is to determine the proper assignment of operators to assembly tasks, in order to balance their workload and decrease the idle times caused by the varying processing times, shifting bottleneck —based on the assembled product variant— and reject rates, resulting in uncertain extra capacity requirements. This step assumes that the lines are balanced, more specifically, assembly tasks are already assigned to workstations, however, throughput of the lines can be adjusted by allocating different operator headcount based on the workload determined by the order stream. The capacity control of the lines specifies the assignment of operators to different tasks. In this case, the general scheme of assembly lines is applied to determine the assignment of operators to assembly, rework and final assembly tasks. The capacity control takes the operator headcount as an input, and specifies the operator-task assignments, considering that several tasks can be assigned to a single operator. Moreover, assignments are many-many type ones, meaning that an operator might perform more tasks, and a given task can be assigned to more operators. In order to determine the proper capacity controls for each product and possible headcount, discrete-event simulation models of the assembly lines are applied. Even though state-of-the-art assembly systems are usually equipped with advanced sensor network, the real workload of the operators is hard to be monitored. The DES models of the lines can provide reliable results about the workloads, and several various control policies can be evaluated. In industrial practice, standard work instructions and corporate policies define how to operate the lines with a given operator headcount, however, these methods are all based on norm times and idealistic data. In order to define efficient capacity control with reduced losses, the underlying stochastic processes have to be considered.

The main advantage of using simulation in this case is the models' capability of representing the stochastic nature of manual processing times and reject rates, identified as the root-causes of excess capacity requirements and unbalanced workloads. The objective is to determine the best assignment policies for each product variant and each possible of operator headcounts. The number of operators can be changed between the consecutive time periods according to the production rates, however, several production lots are released in one shift requiring different operator-task assignments, while the number of operators cannot be changed. In order to select the proper capacity control, several random-generated, but possible control scenarios are analyzed. The main output of the simulation analysis are the utilization of operators and the output rates of the lines. The control policies are determined by simulating the production of a single product type with different control modes, from which the best ones can be selected based on the objective that is usually case-dependent. Based on the results of simulation experiments, the proper controls can be selected for each product type and operator headcount.

5.4.3 Prediction of the capacity requirements with regression models

In flexible, manually operated assembly systems, the prediction of capacity requirements is often complicated, due to the variety of product types and the deviation of processing times. Though, either stochastic or robust optimization models can be applied to cope with non-deterministic parameters (see Section 2.5.2), they require high computation efforts and special solver algorithms that are usually unavailable for most companies. Additionally, diverse reject rates of product variants and therefore varying rate of rework also increase the complexity of planning problems.

In order to tackle these challenges, a production planning model is proposed calculating simultaneously the near-optimal production plan and the corresponding capacity plan, defining the headcount of human operators, while taking into account the aforementioned factors. The essence of the method is the introduction of actual capacity requirements as general functions of products assembled in the same period. These functions are approximated by regression methods, and then integrated directly in a production planning model, facilitating in a robust, proactive approach. In order to approximate the real capacity requirement $Q(\overline{q}_t)$ of a given production lot mix assigned to the same period, a multivariate linear regression model is proposed. The efficiency of applying regression models for capacity planning in an uncertain environment was shown by Gyulai and Monostori (2014), Gyulai et al. (2015) and Gyulai et al. (2017b). The input variables of the regression are the volume q_{pt} of product p to be assembled in period t, and the output is the total manual time $Q(\overline{q}_t)$, required to assemble products within the period. As stated in section 5.4.1, the training dataset of regression models is provided by the simulation model of assembly lines, applying MES log data to represent the actual values and distributions of the production parameters. The simulation is executed to analyze various possible scenarios, projecting the system's expected future behavior from any certain point of time (query time of the log). The applied regression function is defined by (5.1).

$$Q(\overline{q}_t) = \beta_0 + \beta_1 h_t + \sum_{p \in P} \beta_p q_{pt} \tag{5.1}$$

Fitting the above linear function on a simulation-provided dataset, the actual capacity requirements (including rework rates, machine downtimes, operator movements and capacity control related effects) of batches assembled in the same shift can be estimated. In order to obtain enough representative observation for the regression, the simulation analysis is executed on a virtual, big order set, including various lot sizes for all products. In this way, the future behavior of the system under various condition can be projected from its actual status. In the experiments, the simulation model already apply the capacity control setting and scenarios, defined in the preceding step (Section 5.4.2). This enables to apply the best-practice control modes in higher level production planning decisions, to reduce the possible losses related to the execution of plans. Performing the regression, the function approximating the actual capacity requirements can be integrated in the production planning model, as described in the coming section.

5.4.4 Simulation-based robust production planning model

The robust production plan of assembly lines is calculated with an integer programming model (5.2)-(5.8), applying the capacity requirement function $Q(\overline{q}_t)$ as a constraint. The decision variables of the model specify the number of allocated operators h_t for each period, the number of setups y_{pt}, the assembled volumes q_{pt}, and the release of the orders x_{nt}.

minimize

$$\sum_{n \in N} \sum_{t \in T} c_{nt} x_{nt} + c^{\text{set}} \sum_{p \in P} \sum_{t \in T} y_{pt} + c^{\text{opr}} \sum_{t \in T} h_t \tag{5.2}$$

subject to

$$\sum_{t \in T} x_{nt} = 1 \qquad \forall\, n \in N \tag{5.3}$$

$$x_{nt} \leq y_{p_n t} \qquad \forall\, t \in T,\ n \in N \tag{5.4}$$

$$q_{pt} = \sum_{\substack{n \in N \\ p_n = p}} x_{nt} q_n \qquad \forall\, t \in T,\ p \in P \tag{5.5}$$

$$t^{\text{w}} h_t \geq Q(\overline{q}_t) \qquad \forall\, t \in T \tag{5.6}$$

$$h_t \leq h^{\max} \qquad \forall\, t \in T \tag{5.7}$$

$$x_{nt},\ y_{pt} \in \{0,1\}, \quad h_t \in \mathbb{Z}^+ \qquad \forall\, t \in T,\ p \in P,\ n \in N \tag{5.8}$$

The model minimizes an objective function that sums deviation (early delivery and holding), setup and personnel costs (5.2). The constraints specify the fulfillment of each order (5.3), the calculation of setups (5.4) and volumes (5.5), the capacity restrictions (5.6), (5.7) and also the integrity conditions (5.8). The model results in a production plan that gives the required headcount of operators over the horizon, and the assignment of customer orders to production shifts. As stated in Section 5.2.2, setup times are significantly shorter than in the machinery, and also sequencing within a time period is neglected, therefore, a big bucket lot-sizing model is applied in this case.

5.5 Pre-inventory production planning

Due to the applied pull production strategy, the production plan of assembly lines —specifying the lot sizes and release times— directly generates demands for components that need to be available in the inventory to execute the plan by assembling the products. This volume demand is set as a constraint in the planning model of the machinery, however, the objectives of this lot-sizing model are slightly different than those of the assembly lines. Following the general production management and lean principles, the lowest possible component inventory level is desired, and the applied human workforce also have to be minimized. The production planning of pre-inventory segments is formulated by an integer programming model (5.9)-(5.23).

minimize

$$\frac{c^{\mathrm{opr}}}{k}\sum_{o\in O}\sum_{j\in J}\sum_{\pi\in\Pi} r_{oj\pi} + c_n^{\mathrm{h}}\sum_{m\in M}\sum_{\pi\in\Pi} h_{m\pi} \tag{5.9}$$

subject to

$$h_{m\pi} \geq q_{pt} \qquad \forall\, m\in M, \pi\in\Pi, t\in T, p\in P, \pi = kt \tag{5.10}$$

$$h_{m\pi} = h_{m,\pi-1} + \sum_{j\in J} z_{m,\pi-\lceil t_m^{\mathrm{l}}\rceil,j} - d_{m\pi} \qquad \forall\, m\in M, \pi\in\Pi, t\in T, \pi = kt \tag{5.11}$$

$$\gamma_{m\pi j} \leq z_{m\pi j} \qquad \forall\, m\in M, \pi\in\Pi, j\in J \tag{5.12}$$

$$z_{m\pi j} \leq \Theta\gamma_{m\pi j} \qquad \forall\, m\in M, \pi\in\Pi, j\in J \tag{5.13}$$

$$\zeta_{m\pi j} \geq \gamma_{m\pi j} - \gamma_{m,\pi-1,j} \qquad \forall\, m\in M, \pi\in\Pi, j\in J \tag{5.14}$$

$$\zeta_{m\pi j} + \sum_{\substack{\mu\in M\\ \mu\neq m}} (\zeta_{\mu\pi j} - \gamma_{\mu\pi j}) \leq 1 - \gamma_{\mu,\pi-1,j} \qquad \forall\, m\in M, \pi\in\Pi, j\in J \tag{5.15}$$

$$\zeta_{m\pi j} \leq \gamma_{m\pi j} \qquad \forall\, m\in M, \pi\in\Pi, j\in J \tag{5.16}$$

$$\sum_{m\in M} (t_m^{\mathrm{c}} z_{m\pi j} + t_m^{\mathrm{s}}\zeta_{m\pi j}) \leq t^{\pi} \qquad \forall\, j\in J, \pi\in\Pi \tag{5.17}$$

$$z_{m\pi j} = \sum_{o\in O}\omega_{m\pi jo} \qquad \forall\, j\in J, \pi\in\Pi, m\in M \tag{5.18}$$

$$r_{oj\pi} \leq \sum_{m\in M}\omega_{m\pi jo} \qquad \forall\, j\in J, \pi\in\Pi, o\in O \tag{5.19}$$

$$\sum_{m\in M}\omega_{m\pi jo} \leq \Lambda r_{oj\pi} \qquad \forall\, j\in J, \pi\in\Pi, o\in O \tag{5.20}$$

$$\sum_{m\in M}\sum_{j\in J} t_m^{\mathrm{o}}\omega_{m\pi jo} \leq t^{\pi} \qquad \forall\, \pi\in\Pi, o\in O \tag{5.21}$$

$$\sum_{m\in M}\gamma_{m\pi j} \leq 1 \qquad \forall\, j\in J, \pi\in\Pi \tag{5.22}$$

$$z_{m\pi j},\ h_{m\pi},\ \omega_{m\pi jo}\in\mathbb{Z}^+, \quad \gamma_{m\pi j},\ r_{oj\pi}\in\{0,1\} \qquad \forall\, m\in M, \pi\in\Pi, p\in P, j\in J, o\in O \tag{5.23}$$

The objective is to minimize the total inventory and human labor costs over the planning horizon (5.9), while providing enough components for assembly processes (5.10). The balance equation is responsible for linking the consecutive micro periods through the volume of components in the inventory: the inventory level $h_{m\pi}$ in period π equals to the sum of product volumes that were available in the inventory in $\pi - 1$, the parts arriving in the inventory from the machinery (through the shared resources), minus the parts used in the assembly segment (5.11). In the machinery, component-dependent setup times are required to switch the machine from one type to another. These setup times are significantly longer than those of the assembly lines, therefore, setups need to be represented in the model by decreasing the available capacities. In order to consider the setups, indicator variables $\zeta_{m\pi j}$ and $\gamma_{m\pi j}$ are introduced in the model (5.12). In constraint (5.12), Θ parameter links the integer ($z_{m\pi j}$) and binary ($\omega_{m\pi jo}$) variables: it is an arbitrarily chosen big number, and its lower bound is the maximum volume of products that can be produced in period π on a single machine: $\Theta \geq t^{\pi}/\min_{m\in M} t_m^{\mathrm{c}}$. The machines' capacity constraint specifies that the sum of machine processing times and setup times cannot exceed the length of a micro period (5.17). The human workforce capacity limits the number of products that can be machined (5.18)-(5.21). In order to assign the operators to machines and machined products, an additional indicator variable $\omega_{m\pi jo}$ is introduced. Similarly to parameter Θ, Λ is also an arbitrarily chosen big number linking the binary $\omega_{m\pi jo}$ and integer $r_{oj\pi}$ variables, and its lower bound is the maximum volume of products that can be produced in period π on a single machine with a single assigned operator: $\Lambda \geq t^{\pi}/\min_{m\in M} t^{\mathrm{o}}_{m}$. Constraint (5.22) represents the assumption that only a single part type can be produced on each machine within the same period. Additionally, integrity conditions are specified for the necessary decision variables (5.23). In contrast to the case of assembly lines, the production planning model of the pre-inventory processes is a single stage, small bucket lot-sizing model specifying the sequence of production lots and the corresponding operator control as well.

5.6 Numerical results of robust production planning

The viability of the proposed method and robustness of the calculated plans are demonstrated through the results of a use-case from the automotive industry. In the target production system, pre-inventory processes are responsible for producing the main components. First, the steel casts are machined, then deburring and surface treatment processes take place in the shared resources segment. In the machinery, flexible machines are equipped with fixtures that hold several products from the same type, however, setups are required when changing from a certain part type to another, and setup times are sequence-independent. After the machinery and surface treatment, components can be either taken directly to the assembly lines, or kept in the inventory. Regarding the assembly segment, several lines are available for assembling the final products, however, these lines can be planned independently from each other as there are neither material flow, nor shared resources among them. In the subsequent sections, the implementation of the method, and numerical results of the planning workflow are introduced.

5.6.1 Production planning and capacity control of the final assembly lines

The company of the presented case study operates several flexible lines in its final assembly segment. As described earlier, the lines' structure follows a common process pattern, consisting of assembly, testing, rework and final assembly processes with the corresponding workstations. Within the case study, one assembly line was selected, which is a high-runner line with heavy workload and several assigned product types. Important to note that the selected line is a representative subject of the analysis, having all characteristics of the assembly lines (process scheme, data collection) that are essential from production planning viewpoint. Moreover, production plans corresponding to the selected line often tend to be infeasible in the current practice, due to the high variability of capacity requirements, therefore, the development of a robust planning method is of crucial importance to increase the level of effectiveness indicators.

Selection of the proper capacity control policies

According to the specified workflow, the first step towards robust production plans is the selection of proper capacity control policies for the assembly line. As stated in Section 5.2.2, the capacity control defines the assignment of operators to different tasks, based on the assembled product type and allocated headcount. In order to solve this problem, the simulation model of the selected line was applied (implemented in *Siemens Tecnomatix Plant Simulation*), analyzing

Table 5.1. The analyzed control options that define the assignment of operators to assembly (A), final assembly (F) and rework (R) task, including their combinations.

Control No.	Headcount	Operator #1	Operator #2	Operator #3	Operator #4	Operator #5
#1	2	A	FR			
#2	2	AR	F			
#3	3	A	AR	F		
#4	3	A	A	FR		
#5	4	A	A	F	FR	
#6	4	A	A	FR	F	
#7	5	A	A	AR	F	F
#8	5	A	A	A	F	FR

several possible control scenarios (Siemens, 2016). In simulation modeling, validation step of the model building process is essential, in order to make valid conclusions about the performance of the real system, derived from the results of the simulation runs. In the analyzed case, the simulation model of the assembly line was validated by comparing the lot completion times and makespan to real data. The results of an on-site time study and also off-line, historical production logs were applied as basis of the validation, the time frame of the study was a complete week. Evaluating simulation results and comparing them to real data, the model considered to be valid, as the total difference between the real and simulated makespans was only 68 minutes (on a one-week horizon). Relying on this valid simulation model, the best capacity control policies could be determined, defining the operator-task assignment for each product type (assembled on the line) and possible operator headcounts.

The measures applied in this task were the throughput of the line, and a control policy is considered to be better than another if its resulted throughput is higher. Additionally, the statistics (mean, deviation) of operators' workload were also obtained from the experiments, and in case control policies with similar throughput performance were found, the capacity control resulting the highest, well-balanced workload was selected. In each simulation run, only a single product type was analyzed by running the simulation with a fix time-frame. The results of the analysis were summarized in a $p \times (h^{\max} - h^{\min})$ matrix, containing the operator-task assignments with the highest throughput and least idle times for each p and h_t. In the test case, 20 days of production was simulated for all product types, the line can be operated by 2-5 operators. In total, 8 different possible control options were analyzed (Table 5.1), resulting in 72 simulation experiments in total. The outcomes of the analysis were 36 capacity controls, resulting in 90.1% workload per operator during the effective working time.

Prediction of the capacity requirements

The next step of the method is the simulation and regression-based prediction of actual capacity requirements, as norm-time based calculations often fail to give reliable results, due to the stochastic nature of some parameters (e.g. manual processing times), and random events like machine breakdowns or products that fail the functional test. In order to tackle these challenges, multivariate linear regression models were defined for each assembly line, to calculate the overall human workforce, needs to be allocated to the lines to assemble the products in customer-requested volumes. The regression models of each assembly line were defined according to (5.1), the regression coefficients and model parameters were computed by using the *R Studio* environ-

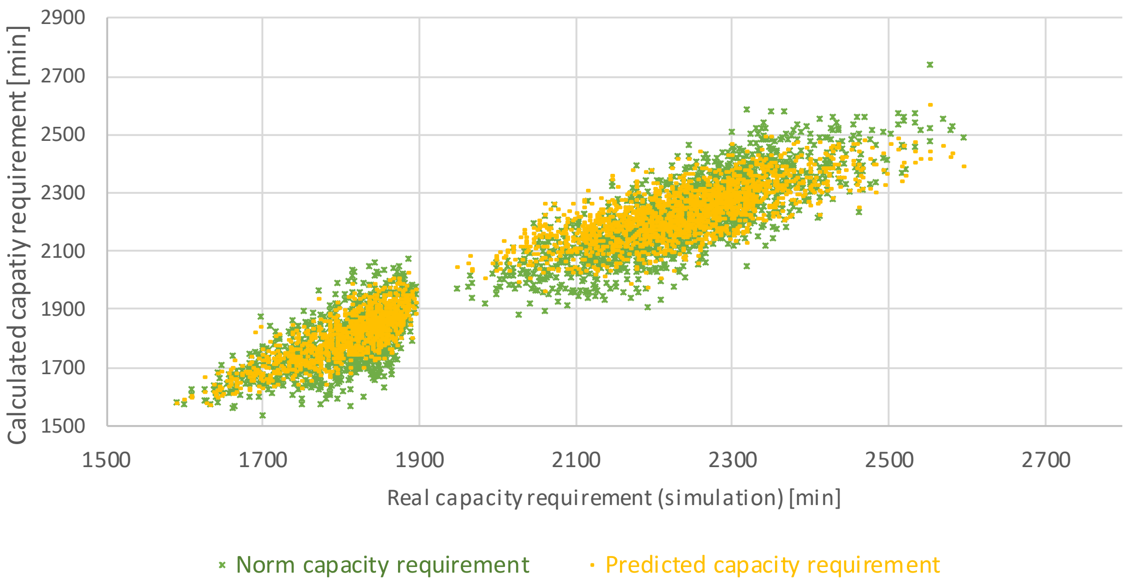


Figure 5.3. Results of the capacity prediction for a sample assembly line.

ment and the general linear regression function `lm` of *R* statistical computing language (R Core Team, 2016), which took less than 1 second to fit the models.

The regression models are built over a dataset, provided by simulation runs as described in Section 5.4.1. As the simulation model applies the latest MES data to obtain the process parameters, it represents precisely the actual physical processes, and capable of providing an arbitrarily large amount of data (in very short time) by simulating the system's behavior in various scenarios. As described earlier, the simulation model was fed with a big production order set, including a large amount of random-generated lots. In order to obtain robust plans by the subsequent calculations, order set needs to be representative enough to cover the whole spectrum of all possible future cases, even the worst case scenarios. Therefore, order sets were randomly generated, considering all products of the portfolio, and applying a uniform distribution on the volumes per order in the range between one piece to the maximal amount of products that can be assembled within one shift. Besides the varying lot sizes, the applied operator headcount was also changed during the experiments, applying the capacity controls determined in the previous step.

During the simulation run, lot completions in each period (production shift) were logged, generating a dataset with the shifts as observations; the assembled volume of each product type, and the corresponding headcount as features of the dataset. In the test case, the simulation provided a production dataset with 4072 shifts that was split up into independent training and sets in $1 : 2$ ratio (1357 and 2794 samples), applying random sampling. In the regression modeling (5.1), the input variables were the product types $p \in P$ assembled on a given line, and the allocated headcount of operators h_t. According to the results, multivariate linear model provides precise prediction for the real capacity requirements, as the coefficient of determination $R^2 > 0.9$ in each of the cases, and for all p values, $p < 2 \cdot 10^{-16}$ indicating that the selected input variables are statistically significant.

On Figure 5.3, the prediction results are visualized by the scatterplots of predicted, and currently applied norm capacity requirements, applying the real capacity requirements as a basis for a sample assembly line. One can infer that the increase of plans' robustness cannot be achieved simply by the adjustment of corporate norm times, as they have a normal distribution error compared to the real capacity requirements, which refers to the fact that currently applied norm times are unable to represent stochastic factors. As the actual capacity requirements exceed the norm time based ones in some cases (norm capacity requirement values are on both sides of the virtual diagonal, equal value line), production planners often apply safety factors in order to keep the expected due dates. Although it might help to maintain the customer-desired service level, it leads to excess capacities and idle times in reality. Moreover, corporate norm times cannot be arbitrarily changed, as they influence several other processes, e.g. product pricing.

Synthetic and real test cases

As for the production planning, two main cases are analyzed in the study: the first set of tests is defined with a proof-of-the-concept purpose, more specifically to highlight the main advantages of the proposed method, compared to other conventional and robust planning methods. In this case, only process related data were gathered from MES to describe the actual status of the line under study, however, artificially generated production planning datasets were applied in order to evaluate the plans under various conditions (e.g. heavy order load). Besides the numerical evaluation of the method, this test case (called *synthetic test*) was responsible for the validation of the models. In the second test case (called *real test*), real historical plans provided by a company, and the calculated robust plans executed with simulation were compared. The reason for evaluating the latter in simulation is justified by the fact that corporate planning policy cannot be simply changed, as it involves other processes, critically affecting the logistics and production performances. In the real test, the planning model introduced in Section 5.4.4 was modified, so as to provide exactly the same output information that the corporate planner software does. In this case, the input and output data of the applied planning model, and therefore the constraints were slightly modified, however, the fundamentals of planning workflow with simulations analysis and the applied capacity function remained the unchanged. In the real test, the simulation-provided KPIs were compared to the historically realized ones as the basis of evaluation.

Robust production planning: synthetic test case

Utilizing the linear function approximation, the above described regression model can be applied directly in the production planning model, implemented and solved in *FICO® Xpress* (FICO, 2017). In the experiments, the optimization algorithms were run until an optimality gap of at most 6% was achieved. In case of the assembly lines, robustness of the plan is highly requested, thus the method was compared to other existing robust planning methods within a comparative study. The basis of the benchmark was deterministic norm time based planning (NTP) applied in most ERP and APS systems. The main difference between NTP and the proposed, simulation- and regression-based robust planning method (RPN) is the calculation of capacity requirements: while in the RPN, the regression model (5.1) is applied in constraint (5.6), the NTP applies norm cycle times to calculate the required human workforce. In NTP, constraint (5.6) has the following form:

$$t^{\mathrm{w}} h_t \geq \sum_{p \in P} t_p^{\mathrm{proc}} q_{pt} \quad \forall t \tag{5.24}$$

Besides the proposed RPN method, the commonly applied, iterative form of simulation-based optimization (as introduced in Section 2.5) was also analyzed on the test case, refining iteratively the capacity requirements after each simulation run. Furthermore, the planning task was also formulated as an integer robust optimization (RO) problem with uncertainty sets (Section 2.5). In the benchmark, a robust counterpart of NTP, called RCT is applied, where cycle times are represented as uncertain parameters with lower and upper bounds. The last analyzed method called RCO is also a robust optimization model, in which the proposed RPN method is reformulated by adding some uncertainty to the regression coefficients, as model fitting always have a certain error. Thus, this method (RCO) can be seen as an extended version of RPN.

In the test cases, a fix-horizon planning problem for a selected final assembly line was investigated, and solved with all methods (NTP, RPN, ITR, RCO, RCT). The input parameters of production planning in the benchmark were customer orders, concerning nine product types assembled on the selected line. In order to provide a comprehensive study, the methods were analyzed applying several planning scenarios that included average, and also complex problem instances. As for the length of the planning horizon, four different cases were tested: $|T| = \{24, 30, 36, 42\}$. In each case, problem instances were generated with different amount of orders: normal, high and extreme order scenarios were analyzed, in which order due dates were uniformly distributed along the planning horizon. In each category of order scenarios, 10 different instances were generated, and solved with all planning methods. Thus, the benchmark included 120 problem instances in total, resulting in 600 solutions given by the five different methods.

Table 5.2. Benchmark of robust production planning methods.

		Lateness [%]					Objective [%]					CPU Time [s]				
$\lvert T \rvert$	Orders	NTP	RPN	RCT	RCO	ITR	NTP	RPN	RCT	RCO	ITR	NTP	RPN	RCT	RCO	ITR
24	Normal	98	73	79	82	83	95	97	100	98	95	8.8	8.8	14.0	14.1	209.2
24	High	100	87	79	83	95	91	94	100	95	91	9.3	10.9	81.5	18.4	90.0
24	Extreme	99	92	$79^{(8)}$	87	97	29	33	$100^{(8)}$	35	30	11.2	131.1	$68.3^{(8)}$	368.3	52.0
30	Normal	100	78	70	73	85	93	96	100	97	93	10.2	11.7	40.4	21.5	141.0
30	High	98	93	81	88	98	84	89	100	91	84	10.9	15.5	370.3	81.0	25.0
30	Extreme	99	90	$86^{(10)}$	$85^{(2)}$	95	22	25	$100^{(10)}$	$29^{(2)}$	23	134.8	517.9	$116.4^{(10)}$	$764.7^{(2)}$	331.7
36	Normal	100	78	75	85	90	93	96	100	97	93	11.4	12.0	61.9	26.7	362.5
36	High	95	93	$84^{(1)}$	87	95	22	26	$100^{(1)}$	30	22	13.8	68.8	659.3	$137.4^{(1)}$	76.1
36	Extreme	95	93	$84^{(9)}$	$87^{(4)}$	95	22	26	$100^{(9)}$	$30^{(4)}$	22	41.6	567.0	$225.9^{(9)}$	$708.1^{(4)}$	184.6
42	Normal	99	87	78	83	93	93	96	100	97	93	13.3	44.6	261.9	86.2	146.7
42	High	99	89	$80^{(5)}$	87	95	49	51	$100^{(5)}$	52	49	16.9	38.7	$1097.2^{(5)}$	240.6	36.9
42	Extreme	97	91	$85^{(9)}$	$88^{(7)}$	98	26	31	$100^{(9)}$	$50^{(7)}$	26	112.2	797.4	$227.6^{(9)}$	$1090.8^{(7)}$	165.1

The benchmark results are summarized in Table 5.2, each row including the average results of 10 problem instances in a given order scenario. The main results are the total lateness, and the objective function value indicating the total costs of production. The values are given in average percentage: when solving a problem instance with the five different methods, 100% corresponds to the method with most lateness and highest cost (in case of both lateness and cost the lower values are the better). Besides lateness and cost, the algorithm's running time is also displayed in seconds. The bracketed superscript values indicate the number of problem instances (out of

10) that a given method could not solve within a time limit of 1800 seconds.

The results show that from robustness viewpoint, the proposed method (RPN) and its robust counterpart (RCO) always outperform NTP method, and the iterative, simulation-based planning. Only the RCT method could result in lower lateness levels, however, it could not solve most of the instances with high or extreme number of orders. Moreover, the latter resulted in very high objective function values (cost), in contrast to RPN that resulted in only slightly higher costs than NTP, thus the cost of robustness in this case is much lower, while it could solve all problem instances (Figure 5.4). As for the calculation times of the methods, robust optimization based methods require high CPU times, while simulation based RPN and ITR have comparable running times (the CPU time of RPN includes the CPU time of fitting the regression model).

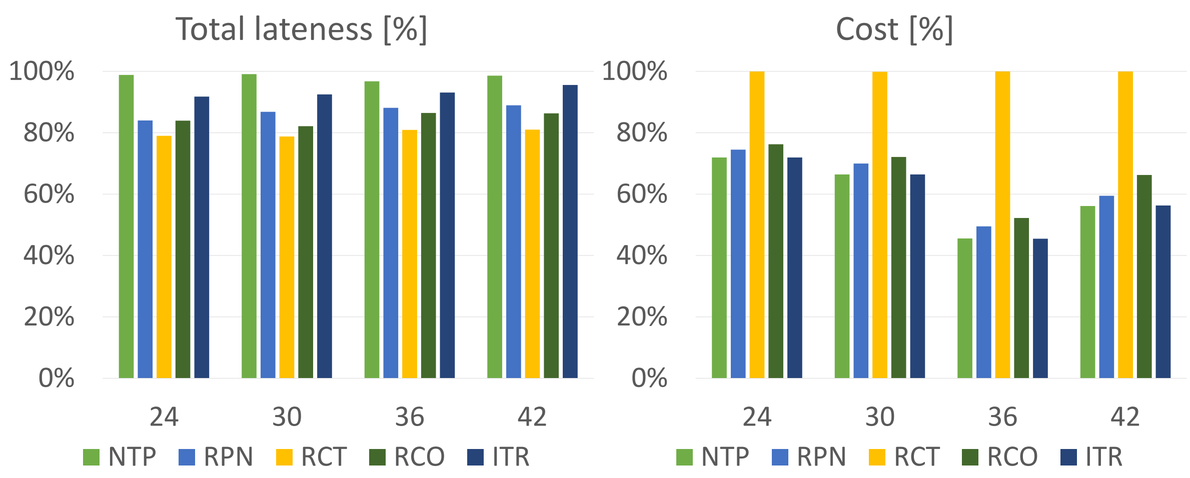


Figure 5.4. Total lateness (left) and cost (right) results of the benchmark with the five different planning methods.

Robust production planning: real test case

In the real test case, simulation and function approximation tools were applied in the same way as in the synthetic test, providing the actual capacity requirements $Q(\overline{q}_t)$ as the main output. In order to obtain plans that are comparable with the corporate ones, the planning model was adjusted in a way that inventory and backlog levels were continuously observed during the planning, and orders were aggregated. The planning was performed on a rolling horizon basis with a one-shift resolution (3 shifts per day). On the test case, five days' plans were calculated and executed in simulation, the planning horizon was 6 shifts long, and the replanning period was set to 3 shifts (following the corporate practice). In order to adjust the plan to reality, initial stock levels and backlogs were set in the beginning of the horizon.

The modified planning model applied in the real test case is formulated by (5.25)-(5.35). The objective function (5.25) minimizes the overall costs of inventory (i_{pt}), setups (y_{pt}), backlogs (b_{pt}), the headcount of operators (h_t) and the number of active shifts (a_t). The variable q_{pt} expresses the amount of product p assembled in period t. Constraint (5.26) transforms individual orders into volume d_{pt} of products to be delivered (aggregate volume, calculated from individual orders) (5.26), and states that customer orders must be fulfilled by delivering the amount s_{pt}

from product p in period t (5.27). The next inequalities constrain the human capacities applying the approximated function $Q(\bar{q}_t)$ of actual capacities (5.28), and controlling the minimal (5.29) and maximal (5.30) headcounts of operators required by the processes (considering the capacity controls defined in Section 5.4.2). Constraints (5.31) and (5.32) calculate the number of setups y_{pt} applying Ω as an arbitrarily chosen big number with the lower bound of the maximal amount of product that can be assembled within one shift: $\Omega \geq (t^{\mathrm{w}} h^{\max}) / \max_{p\in P} t_p^{\mathrm{proc}}$. The number of active shifts —in which at least one batch is assembled— can be calculated by (5.33). Subsequent time periods are linked through the assembly, backlog and inventory volumes of product p in time t and $t-1$ by the balance equation (5.34). The integrity conditions are defined by (5.35).

minimize

$$\sum_{t\in T}\sum_{p\in P}\left(c^{\mathrm{stock}} i_{pt} + c^{\mathrm{set}} y_{pt} + c^{\mathrm{bl}} b_{pt}\right) + \sum_{t\in T}\left(c^{\mathrm{opr}} h_t + a_t\right) \tag{5.25}$$

subject to

$$d_{pt} = \sum_{\substack{n\in N\\ p=p_n\\ t=t_n^{\mathrm{d}}}} q_n \qquad \forall\, t\in T,\ p\in P \tag{5.26}$$

$$s_{pt} \geq d_{pt} \qquad \forall\, t\in T,\ p\in P \tag{5.27}$$

$$t^{\mathrm{w}} h_t \geq Q(\bar{q}_t) \qquad \forall\, t\in T \tag{5.28}$$

$$h^{\min} y_{pt} \leq h_t \qquad \forall\, t\in T,\ p\in P \tag{5.29}$$

$$h_t \leq h^{\max} \qquad \forall\, t\in T \tag{5.30}$$

$$q_{pt} \leq \Omega y_{pt} \qquad \forall\, t\in T,\ p\in P \tag{5.31}$$

$$q_{pt} \geq y_{pt} \qquad \forall\, t\in T,\ p\in P \tag{5.32}$$

$$|P| a_t \geq \sum_{p\in P} y_{pt} \qquad \forall\, t\in T \tag{5.33}$$

$$i_{pt} - b_{pt} = i_{p,t-1} - b_{p,t-1} - s_{pt} + q_{pt} \qquad \forall\, t\in T,\ p\in P \tag{5.34}$$

$$q_{pt}, b_{pt}, s_{pt}, i_{pt}, h_t, a_t \in \mathbb{Z}^+, \quad y_{pt}\in\{0,1\} \qquad \forall\, t\in T,\ p\in P \tag{5.35}$$

As for the input data of planning, five days' production was planned on a rolling horizon, considering orders on hand that were known already in the beginning of the horizon, and also those that are placed by the customers during the five days. Similarly to the previous case, nine product types were assembled, of which orders are placed for 36 variants, however, these variants are not distinguished in the planning model due to the very minor differences in assembly processes. In the model, order fulfillment from inventory, as well as backlogging were options similarly to the synthetic test case, however, in this real planning case, different measures were applied to compare the results. The KPIs were the main corporate efficiency measures: the total output (O^{total}) and the applied human workforce expressed in operator-minutes. The latter is approximated with the function $Q(\bar{q}_t)$, and denoted by Q in the results below. Besides, the average output per operator and per shift O^{op} was also derived from the previous two values. Due to the normal order load of the analyzed period, significant amount of backlogs were not realized, and both plans had similar performance from this perspective. Results on the lateness —applied as a KPI in the synthetic test— were not available in the real case, as related data were not logged in the ERP system. The main results of the real test are summarized in Table 5.3.

Table 5.3. Results of the real test case of robust production planning.

	NTP (historical)			RPN (simulation)		
	O^{total} [pcs.]	Q [min]	O^{op} [pcs.]	O^{total} [pcs.]	Q [min]	O^{op} [pcs.]
Day1	385	4335	42.63	203	1570	62.06
Day2	553	3197	83.03	492	3533	66.84
Day3	605	5532	52.49	630	4421	68.40
Day4	655	5177	60.73	636	3833	79.65
Day5	635	5118	59.55	225	1658	65.14

As for the test results, one might remark that the difference of historical and robust plans' total output (summed over the five days) is significant. This difference is resulted by the inventory volumes, as in the reality, 641 pieces were planned to make to stock, in addition to the customer orders. The total order volume for the five days was 2192, which is quite similar to the produced volume of 2186 pieces, achieved by the proposed robust planning. In the current settings of the planner model, inventory levels are minimized (safety stocks are allowed to be set), therefore, products are only kept in the inventory if any order within the planning horizon is fulfilled from stock. From this perspective, the RPN method resulted a plan that match the expectations. As for the operators' performance and workload, substantially better results were achieved by the RPN method, as the average output per operator is 68.4 pieces, compared to the historical value of 59.6 pieces. This increase in efficiency is resulted by the combination of the improved capacity control, as well as its application in the planning model. In this case, production plan optimized so as the mix of production lots assembled within the same shift is selected to be in balance with the expected capacity requirements considering the possible negative effects of stochastic parameters. Conclusively, applying the RPN method in scenarios with normal order load (in the test case, the line was operated on 60% of its full capacity) results in increased output with extra allocated human workforce, compared to the NTP method.

5.6.2 Production and capacity planning of the pre-inventory processes

The production planning model of pre-inventory processes (Section 5.5) is responsible for calculating the production lot sizes $z_{m\pi j}$ and the corresponding shift plans with the operator-machine assignments $\omega_{m\pi jo}$, to ensure that the components required by the final assembly lines will be available in the inventory on time. In order to analyze various resulted production plans in detail, the DES model of the pre-inventory segment was applied, simulating the machining, deburring and surface treatment processes. The characteristics of the test system are detailed in the followings. In the machinery, $|J| = 11$ flexible machines are available, and $|M| = 14$ different main component types are produced. The resolution of the plans is 2 hours, therefore, $\rho = 4$ and $t^\pi = 120$. The main parameters of the components are summarized in Table 5.4. In addition to the demands generated by the assembly plan of the analyzed line, demands for the other components were randomly generated by uniform distribution with the following bounds: $120 \geq d_{m\pi} \geq 200 \quad \forall m \in M, \pi \in \Pi, t \in T, t^\pi = \frac{t^{\text{w}}}{\rho}$. The production planning model (introduced in Section 5.5) was implemented in *FICO® Xpress*, and solved by its default branch and bound solver, with the stopping criterion that the optimality gap should be at most 6%. The average running time of the solver algorithm was 180 seconds (FICO, 2017).

Table 5.4. Component parameters in the test case.

M	t^{l}_m	t^{c}_m	t^{o}_m	h_{m0}	t^{s}_m
Component1	1.22	0.76	0.6	127	32
Component2	0.59	1	0.75	131	30
Component3	2.14	0.81	0.53	101	32
Component4	1.28	0.76	0.8	140	50
Component5	0.16	0.86	0.56	123	30
Component6	2.57	0.83	0.56	115	25
Component7	1.65	0.7	0.56	121	29
Component8	1.82	0.66	0.78	113	57
Component9	2.67	0.9	0.78	108	20
Component10	1.56	1	0.81	104	41
Component11	1.78	0.95	0.78	106	22
Component12	2.34	0.68	0.56	111	52
Component13	0.31	0.86	0.8	144	53
Component14	2.77	1	0.8	119	52

In order to analyze the performance of the planning method if some of the parameters are stochastic, a sample production plan was executed with simulation. In case the calculated plans cannot be executed properly, final assembly of products will be delayed, resulting in late order completion. In the analysis, different production scenarios were compared, in which lead times t^{l}_m, manual processing times t^{o}_m and machine availability A were modified to posses a certain deviation instead of being deterministic. Machine availability is the percentage of time, during which a machine can be used for production. The main measures were the total backlogs realized at the inventory when demands of final assembly lines were not satisfied. In this case, the total (B^{t}) and percentage (B^{p}) amount of backlogs were observed:

$$B^{\mathrm{t}} = \sum_{\pi \in \Pi} \sum_{m \in M} \left(d_{m\pi} - z^{\mathrm{sim}}_{m\pi} \right) \tag{5.36}$$

$$B^{\mathrm{p}} = \frac{B^{\mathrm{t}}}{\sum_{\pi \in \Pi} \sum_{m \in M} d_{m\pi}} \tag{5.37}$$

where $z^{\mathrm{sim}}_{m\pi}$ is the total volume produced of component m in period π resulted by the simulation analysis. In the test scenarios, the effect of uncertain lead and manual operation times were analyzed by representing them as stochastic variables with normal distributions, specified by the mean (μ) and standard deviation parameters (σ). In each scenarios, the standard deviation of time parameters were set to 10% of the mean value: $\sigma = 0.1\mu$. The input parameters of the test scenarios and the corresponding simulation results are summarized in Table 5.5.

According to the test results, the proposed planning method is able to produce the expected outcome, more specifically to plan the production of the pre-inventory processes in a way to provide enough components for the final assembly processes without backlogs. In this way, the smoothness of production can be maintained, and the execution of production plans, calculated for the final assembly lines, is independent of the pre-inventory processes in most of the test scenarios. In some of the scenarios, backlogs occur during the execution, which means that the final assembly of products cannot be started on the planned time. Although it would cause problems in a real production situation, backlogs only occur in scenarios with extreme parameters (e.g. processing times increased by 60%), and the amount of realized backlogs in those cases are also relatively low.

Table 5.5. Simulation analysis: execution of the production plans (pre-inventory processes).

Scenario	μ^{lead}	μ^{op}	A[%]	B^{t}[pcs.]	B^{p}[%]
1	1	1	86	0	0.0%
2	1	1	93	0	0.0%
3	1	1	100	0	0.0%
4	1	1.30	86	0	0.0%
5	1	1.30	93	4	0.0%
6	1	1.30	100	0	0.0%
7	1	1.60	86	111	0.8%
8	1	1.60	93	255	1.9%
9	1	1.60	100	111	0.8%
10	1.30	1	86	5	0.0%
11	1.30	1	93	5	0.0%
12	1.30	1	100	5	0.0%
13	1.30	1.30	86	5	0.0%
14	1.30	1.30	93	42	0.3%
15	1.30	1.30	100	5	0.0%
16	1.30	1.60	86	196	1.5%
17	1.30	1.60	93	336	2.5%
18	1.30	1.60	100	196	1.5%
19	1.60	1	86	55	0.4%
20	1.60	1	93	74	0.6%
21	1.60	1	100	55	0.4%
22	1.60	1.30	86	110	0.8%
23	1.60	1.30	93	262	2.0%
24	1.60	1.30	100	110	0.8%
25	1.60	1.60	86	492	3.7%
26	1.60	1.60	93	599	4.5%
27	1.60	1.60	100	492	3.7%

5.6.3 Discussion of the results

When discussing the planning results, important to keep in mind that several existing definitions of robustness is applied in practice, as discussed in Section 2.5. In this research, the solution is considered to be robust in case it is feasible under the considered variation of influencing factors, and its deviation from a target is small enough. As the training dataset of the regression model contains extreme order scenarios, the above definition is in line with minimax approaches, seeking solutions that minimize the maximal losses of worst case scenarios. The objective function of the planning model is composed of inventory, setup and personnel costs, thus scenarios' excess costs are reflected by the cost of robustness, when different planning methods are compared. In general industrial practice, it is a managerial decision whether it is worth for a company paying extra amounts to increase the plans' robustness, however, it is proven by the benchmark results that the cost of robustness is not really significant if the RPN method is applied. More specifically, the robustness of planning can be increased by 11% in average, for additional costs of 3%, which is a considerable advantage compared to other analyzed robust planning methods. Besides, the CPU time of the solver (together with the data analysis) in normal and high order numbers is only increased by 10 seconds in average, moreover, a robust plan can be obtained with RPN within maximum 800 seconds even in the hardest problem instances with extreme orders. It is also important that robustness cannot be simply increased by adjusting the norm cycle times (Figure 5.3), but the target delivery performance can be provided by properly combining production lots with the proposed, proactive robust planning method (5.4.4). While in RPN planners do not have to take care about adjusting the simulation and planning parameters due to the data import from MES, it is important to carefully preset the uncertainty sets in robust optimization models, which is not possible in several cases. As for the main results, one can conclude that robustness of the plans in the synthetic case could be increased significantly by 11% in average, without much extra efforts, which is a considerable advantage of the RPN method, and the idle times in this case could be decreased by 14%. In the real test case, the productivity could be increased by 14% in average, applying the proposed method in a planning problem with normal order load conditions, which equals to the amount of idle times reduction realized in the synthetic case. Conclusively the method is considered to meet the expectations, even in real cases.

The main benefit of the proposed workflow is its ease of integration in the existing planning workflow without significant modifications in the models. For companies applying MES and ERP or APS systems, accessing and loading the data in the analysis model by queries can be done with minimal efforts, without any special requirements. The major prerequisite of applying the proposed robust planning workflow is the simulation model of the assembly lines, which however can be quickly built if a common process scheme and thus model structure can be identified. In the planning model, modifications and additional tools are not necessary, as only the capacity requirements need to be changed and other parts of the model remain unchanged, in contrast to robust optimization tools that require special solver engines that are usually not available at companies. From implementation point of view, the tool itself is flexible and does not require hard-wired heuristics, besides, the simulation model itself can be also used for multiple purposes: e.g. defining the capacity control modes or projecting the future behavior of the system in various conditions. Thanks to the MES connection, the models always utilize up-to-date production data, while able to consider the stochastic nature of processes and parameters, which is not possible in the current norm time based planning.

5.6.4 Implementation of the method

As described in the previous sections, the elements of the robust production planning workflow were implemented in different, special software tools (DES, statistics/learning and optimization), and a desktop application was used as an environment that implement the data flow and link among these tools. In parallel, the method was also integrated in the Simulation and Navigation Cockpit, introduced already in Section 4.4.3. Within the integration, the implemented models were used as calculation tools and various interfaces were applied (ODBC, file interface) to implement links with the central database of the cockpit. The robust planning workflow is implemented with three loops in the cockpit (Figure 5.5): a capacity control loop, an assembly and a machinery planning loops. Once the ERP and MES data are loaded in the central database, the capacity control loop is executed first, in oder to identify the capacity controls to be used,

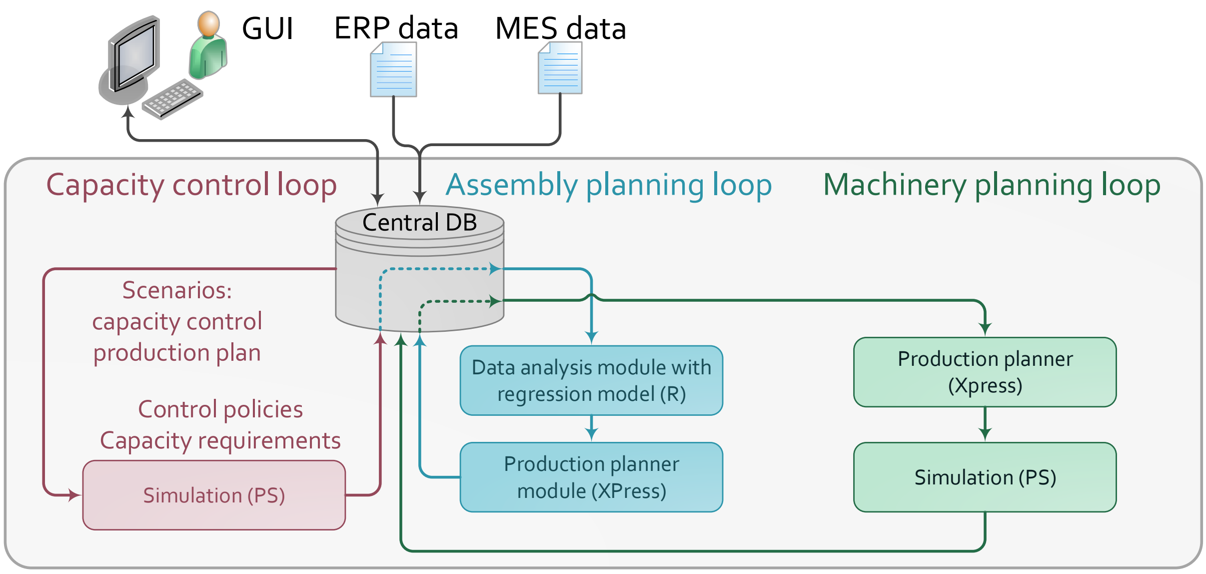


Figure 5.5. Robust planning method in the Simulation and Navigation Cockpit.

and also to generate data for the regression modeling. Within this step, only the simulation model of the assembly line is applied. Once the capacity related data is available and stored in the DB, the assembly planning loop can be executed. In this step, two models are linked applied: the data analysis model implementing the function approximation, and the production planner model to calculate robust plans. The regression models are built over the simulation results, and they are integrated in the production planner module that implements the mathematical model. The calculated plans and also the models are saved in the DB, for the sake of re-usability in future experiments. Additionally, assembly plans are also used in the machinery planning, in which the production plan of the machinery is optimized first then the result is evaluated immediately by running a simulation experiment. Next to the control of the data flow, the central DB is responsible for managing the experiments created when using the cockpit. An experiment in the software is a single analysis with individual parameters and results, both saved in the DB. Experiments with similar characteristics and objective are gathered in a scenario, which is the fundamental object in the cockpit for storing and reloading analysis parameters and the results. Thanks to the web-based architecture, all models run on the server side, and the whole planning workflow can be controlled via the web-based graphical user interface of the framework.

5.7 Summary of Chapter 5

In Chapter 5, a new method was introduced to support the robust production planning of flexible final assembly lines in a proactive way. As these lines are often the last stage of the production, the proposed planning method was completed by the planning models of the preceding stages in the process chain, assuming that pull strategy is applied. In order to harmonize the production of different stages, the planning problem was decomposed at the in-process inventory, accordingly, the method was split in two main phases: first, the production plans of the final assembly lines were calculated, then the production planning of the pre-inventory processes was done, considering already the demands generated by the solution of the preceding step. In the phase of final assembly planning, a simulation-based optimization method was applied to manage stochastic variables and random events in a mathematical model, without increasing its computation complexity and running time. The rationale of the approach relies in the quasi-real-time data that can be gathered from the MES system about the actual status of the system and processes. This data is then used for projecting the actual status of the system to a large set of possible future scenarios, to obtain information and predict parameters that are essential in robust production planning. Therefore, regression models were applied to predict the actual capacity requirements of different production scenarios, instead of calculating the plans according to idealistic, norm cycle times. Besides the production planning, the simulation models of assembly lines were applied to determine the proper control policies of the lines, resulting in reduced idle times and balanced operator workloads. The performance of calculated plans was analyzed by executing them in a simulation environment, representing the possible random events and stochastic parameters. According to the test results, the proposed planning method provides robust production plans, and performs well in a real production environment. Important part of the proposed method is the material supply planning, following the pull production strategy. In the pre-inventory planning model, the objective was to minimize the components' inventory cost, while providing the parts that are required by the final assembly lines. The operator-machine assignment problem was also solved to decrease the human capacity requirements of production. According to the results, the proposed method is suitable for planning in a way that the continuousness of the production along the whole process chain can be ensured, and customer expected service-level can be maintained.

Regarding the definition and measure of robustness, and interpretation of the results, important to highlight that plans' robustness in the proposed method is provided by the prediction of system's behavior in future cases, assuming that the system's actual state in the near future won't change significantly. For the projection of the system's state to this near future, up-to-date MES data and a simulation model are applied, via the use of regression models. These models are built upon a finite set of realistic orders that certainly provide a representative sample set of possible future scenarios. The order sets are randomly generated, considering all products of the portfolio, and applying a uniform distribution on the volumes in the range between one piece to a possibly high amount of products per oder. Although this scenario generation will certainly provide a representative training set, by nature, it might affects the training results, and therefore, the quality of plans. In this regard, important to highlight that robustness of plans is not directly guaranteed by applying the method, but will certainly take effect if the training set is generated carefully, by including a satisfactory high number of samples that represent and cover the possible future order streams.

As for the future work related to the presented robust planning method, the following directions are identified. First one is the analysis of different, commonly-applied manufacturing systems like machine flow-shops, where lead time is one of the most important planning parameters. Pfeiffer et al. (2016) highlighted that data analytics tools can be applied on shop-floor data to accurately predict the lead times and to calculate robust production plans upon. In that case, additional prediction parameters need to be considered like work-in-progress or buffer levels. Also important direction of future work is the broader analysis of robustness, as discussed in Section 2.5.1. Interesting related task is the sensitivity analysis of various production parameters on the execution robustness of the plan, involving also objective function elements other than costs, e.g. natural planning measures like work in progress or resource utilization. Besides, another promising direction towards robustness is the application of new function approximation techniques that can be combined with mathematical optimization tools. In case of complex relations among the parameters, piecewise linear regression models might be suitable to predict the target parameters while keeping the linearity of the optimization model.

Chapter 6

Conclusions and outlook

In Chapters 3-5, new scientific results were presented to solve capacity management and production planning problems, often emerge in today's practice when reconfigurable and flexible assembly systems are applied. As discussed, these systems offer cost efficient solutions for managing product variety, however, their advantages can be utilized only if system structure is continuously matched with the order stream to sustain the internal efficiency and customer-expected service level, applying proper production and capacity planning methods. In the thesis, the new scientific results were derived to meet these requirements as summarized in Section 6.1.

6.1 New scientific results

The research presented in the thesis is summarized in four thesis statements (Thesis 1-4, presented in Sections 6.1.1-6.1.4). The first two statements related to the framework defined for capacity management of modular assembly cells in Chapter 3. Thesis 3 presents the main results achieved in relation with production and capacity planning of reconfigurable, robotic assembly cells, while Thesis 4 highlights the main scientific contribution to robust production planning and capacity control of flexible assembly systems.

6.1.1 Strategic level system configuration and product-resource assignment in modular assembly systems

In Section 2.3, modularity was defined as an umbrella concept to manage dedicated, flexible and reconfigurable manual assembly systems in a common methodology. Grounding on this, a comprehensive framework was presented in Section 3.4, offering solutions for capacity management of modular systems on each level of the classical planning hierarchy. On the highest, strategic level, the long-term system configuration problem was solved to determine the required investments, and product-assembly system assignment based on the order stream forecasts and the actual system configuration. The main driver of these decisions is the minimization of production-related costs, taking into account different cost elements that are characteristic to dedicated, flexible and reconfigurable resources. It was identified that there is no rule of thumb for assigning products to either of these system types, as the overall costs —incur on the long run— are affected by multiple factors that are in strong correlation with the lower, tactical level decisions. This is mainly resulted by the dynamic processes characterizing the operation of these systems, and mainly valid for flexible and reconfigurable resources.

Therefore, a simplified version of the system configuration problem —called line assignment— was solved first, assigning products to dedicated or reconfigurable lines on a cost basis. A two-level model was proposed and applied as a proof-of-the-concept that cost factors considered on the strategic level can be predicted with function approximation model, defined over a set of solutions of virtual, tactical level planning problems. Grounding on this, the comprehensive system configuration method was defined for modular assembly systems, applying an optimization model in which elements of the objective function and some of constraints are represented by approximation functions. The training set of regression models were obtained by solving the tactical level production planning problem on a representative set of virtual scenarios. The new scientific results in relation to the system configuration of modular assembly systems were summarized in the first thesis statement as it follows highlighted.

Thesis 1: In the capacity management framework of modular asssembly systems with heterogeneous resources, the strategic level resource assignment and system configuration problem can be solved with the following integer optimization model. In the model, the prediction of operational costs is performed by regression, and the training sets of regression models are provided by the solutions of the tactical level planning model applied on virtual scenarios. The general scheme of the optimization model is the following:

minimize

$$\boldsymbol{\Psi}\left(z^s_{pu}, w^s_{pu}\right) + \boldsymbol{\Theta}\left(z^s_{pu}, w^s_{pu}\right) + \boldsymbol{\Gamma}\left(z^s_{pu}, w^s_{pu}\right) + \boldsymbol{\Lambda}\left(z^s_{pu}, g^s_{bu}\right) \tag{6.1}$$

subject to

$$\sum_{s\in S} z^s_{pu} = 1 \qquad \forall\, p \in P,\ u \in U \tag{6.2}$$

$$w^s_{pu} \geq z^s_{pu} - z^s_{p,u-1} \qquad \forall\, p \in P \tag{6.3}$$

$$g^s_{bu} \geq z^s_{pu} \qquad \forall\, b \in B = \{1 \dots p_b\} \tag{6.4}$$

$$\boldsymbol{\Phi}\left(z^s_{pu}\right) \leq h^{\max} \qquad \forall\, p \in P,\ u \in U,\ s \in S \tag{6.5}$$

$$\boldsymbol{\Upsilon}\left(z^s_{pu}\right) \leq m^{\max} \qquad \forall\, p \in P,\ u \in U,\ s \in S \tag{6.6}$$

$$z^s_{pu} \in \{0,1\} \quad w^s_{pu} \in \{0,1\} \quad g^s_{bu} \in \{0,1\} \qquad \forall\, p \in P,\ u \in U,\ s \in S,\ b \in B \tag{6.7}$$

In the objective function (6.1), $\boldsymbol{\Psi}$, $\boldsymbol{\Theta}$, $\boldsymbol{\Lambda}$ and $\boldsymbol{\Gamma}$ express depreciation, change of assignment, investment and operation costs, respectively. Constraints (6.2)-(6.4) guarantee the feasibility of the solution, while (6.5) and (6.6) are technological constraints, bounding the utilization of human (6.5) and machine (6.6) resources. The nonlinear $\boldsymbol{\Psi}$, $\boldsymbol{\Theta}$, $\boldsymbol{\Lambda}$ and $\boldsymbol{\Gamma}$ functions can be approximated by linear regression models, applying solutions of the tactical level planning model solved on a representative set of virtual scenarios. In this way, the linearity of the overall optimization model can be guaranteed. The input parameters of regression models are the capacity requirements of products (time), and the number of different product types assigned to various system types. The decision variable z^s_{pu} specifies if product p in period u is assembled in system s, and g^s_{bu} expresses if all elements of an arbitrarily chosen subset b of products are assembled in system s in period u.

6.1.2 Tactical level production and capacity planning of modular assembly systems

The main decisions in tactical level production planning of modular assembly systems concern the calculation of production lot sizes to match internal capacities with customer orders. Regarding dedicated and flexible resources, some planning methods exist already to solve related problems, however, there is no standard way of solving the combined production and capacity planning problem of modular, manual assembly systems. In Section 3.4.2, a new, generic model was defined to solve the above problem that can be also applied to provide a training set for cost predictions in the strategic system configuration model. In such cases, capacity constraints are applied so as to enable expansions if needed. The integer optimization model of tactical level production and capacity planning problem is defined as it follows.

Thesis 2: The tactical level production and capacity planning problem of modular reconfigurable assembly systems is expressed by the following model, minimizing the operation costs while considering both human and machine resources.

minimize

$$\sum_{t\in T} c^{\mathrm{opr}} h_t + \sum_{p\in P}\sum_{t\in T} c^{\mathrm{set}} y_{pt} + \sum_{t\in T}\sum_{n\in N} c_{nt} x_{nt} + \sum_{t\in T}\sum_{n\in N}\sum_{j\in J} c^{\mathrm{opn}} x_{nt} r_{jp_n} \qquad (6.8)$$

subject to

$$\sum_{t\in T} x_{nt} = 1 \qquad \forall\, n \in N \qquad (6.9)$$

$$n_j \le r_j^{\mathrm{avail}} \qquad \forall\, j \in J \qquad (6.10)$$

$$\sum_{p\in P} r_{jp} y_{pt} \le n_j \qquad \forall\, j \in J,\ t \in T \qquad (6.11)$$

$$x_{nt} \le y_{pt} \qquad \forall\, t \in T,\ p = p_n,\ n \in N \qquad (6.12)$$

$$\sum_{n\in N} x_{nt} t_p^{\mathrm{proc}} + y_{pt}(t_p^{\mathrm{rec}} + t_p^{\mathrm{set}}) \le h_t t^{\mathrm{w}} \qquad \forall\, t \in T,\ p = p_n \qquad (6.13)$$

$$h_t \in \mathbb{Z}^+ \quad n_j \in \mathbb{Z}^+ \quad y_{pt} \in \mathbb{Z}^+ \quad x_{nt} \in \{0,1\} \qquad \forall\, j \in J,\ t \in T,\ n \in N,\ p = p_n \qquad (6.14)$$

In the model, J, T, P, and N are the sets of resources, time periods, products and orders, respectively. The cost parameters are denoted by c, t_p^{proc} is the total capacity requirement of product p, while t_p^{rec} and t_p^{set} are the reconfiguration and setup times of product p. The product of order n is denoted by p_n, r_j^{avail} is the amount of available of modules and r_{jp} is the required amount of modules from type j by product p. Decision variables x_{nt}, y_{pt}, h_t and n_j express the execution of orders, necessary setups, operator headcount and the applied modules in planning period $t \in T$, respectively. In the objective function (6.8), c^{opr}, c^{set}, c_{nt} and c^{opn} parameters express the costs of operators, setups, due date deviation and operation, respectively. The constraints limit the execution of orders (6.9), module consumption (6.10-6.11), setups (6.12) and operator headcount (6.13). Introducing an additional element $\sum_{j\in J} n_j c_j^{\mathrm{m}}$ in the objective function enables to add new modules to the resource pool if requested, therefore, the model can be applied to solve virtual production planning scenarios, supporting the solution of strategic level system configuration. In such cases, c_j^{m} expresses the purchase cost of modules, and

(6.11) needs to be disregarded.

$$\sum_{t\in T} c^{\mathrm{opr}} h_t + \sum_{p\in P}\sum_{t\in T} c^{\mathrm{set}} y_{pt} + \sum_{t\in T}\sum_{n\in N} c_{nt} x_{nt} + \sum_{t\in T}\sum_{n\in N}\sum_{j\in J} c^{\mathrm{opn}} x_{nt} r_{jp_n} + \sum_{j\in J} c_j^{\mathrm{m}} n_j \quad \textbf{(6.15)}$$

If the planning problem is formulated as a small-bucket model that does not allow for reconfiguring the system within a given time period, the number of reconfigurations can be minimized by solving a traveling salesman problem (TSP). The vertices of the weighted state-space graph represent the time periods, and the weights of edges can be calculated applying a distance function on two products' resource requirements, produced in consecutive time periods. The solution of this model a time-indexed plan, specifying production lot sizes and the corresponding resource usage. Slightly modifying the decision variables, a new model can be obtained that specifies the production lot sizes, moreover, the headcount of operators allocated to assemble the orders. Applying this reformulation, the operational level problem can be defined and solved with the objective of minimizing the overall operator headcounts within each time period, considering that operator skills are flexible, so as they are capable of switching between assembly tasks within a given period.

6.1.3 Capacity management of modular, robotic assembly cells

As highlighted in Chapter 4, modular, automated assembly cells are also gaining practical relevance in industrial applications, as they offer cost efficient solution to assemble products in high variety. However, due to the different assembly processes that mostly include various joining technologies (e.g. welding, clinching etc.), modular robotic assembly cells are mostly applied instead of manual systems. A new production planning method was proposed in Section 4.4.2 that can be applied for the estimation of operational costs, already in the early design stage of robotic assembly cells, composed of static, and also reconfigurable, modular elements. The planning model is combined with a DES model in a tool called *Production Planning and Simulation Tool*, which is part of a workflow that supports design, management and operation of reconfigurable assembly cells (Figure 4.2). The overall concept and methodology are results of a collaborative work. The framework consists of four main tools with the corresponding decisions and problem instances. The first tool, called *Assembly System Configuration Tool* is developed by the University of Twente[1]. The second tool, called *Assembly Cell Configuration Tool*, and the *Reconfiguration Planning Tool* incorporating and utilizing the results of all other tools are developed by Politecnico di Milano[2]. The own scientific results were achieved within the definition and development of the *Production Planning and Simulation Tool*, summarized in Thesis 3.

Thesis 3: The operation costs of modular, robotic assembly cells can be predicted efficiently already in their early design stage, applying mathematical optimization based production planning, and discrete-event simulation to execute the calculated plans. The input parameters of planning are customer order forecasts and technological data of the cell. Based on the forecasts, the expected production

[1] Corresponding researchers are Johannes Unglert and Juan Manuel Jauregui Becker from University of Twente, Enschede, The Netherlands

[2] Corresponding researchers are Massimo Manzini, Marcello Urgo and Marcello Colledani from Politecnico di Milano, Milan, Italy

lot sizes can be calculated with the following model:

$$\textbf{minimize}$$

$$\sum_{p\in P}\sum_{t\in T}\left(c^{\text{bl}}b_{pt}+c^{\text{stock}}i_{pt}\right) \tag{6.16}$$

$$\textbf{subject to}$$

$$s_{pt}\geq d_{pt} \qquad \forall\, p\in P,\ t\in T \tag{6.17}$$

$$\sum_{c\in C}\sum_{p\in P} r_{jp}y_{ptc}\leq r_j^{\text{avail}} \qquad \forall\, t\in T, j\in J \tag{6.18}$$

$$\sum_{p\in P}\left(t_m^{\text{c}}x_{ptc}+t_m^{\text{s}}g_{ptc}\right)\leq t^{\text{w}} \qquad \forall\, c\in C, t\in T \tag{6.19}$$

$$i_{pt}-b_{pt}=i_{p,t-1}-b_{p,t-1}-s_{pt}+\sum_{c\in C}x_{ptc} \qquad \forall\, p\in P, t\in T \tag{6.20}$$

$$g_{ptc}, y_{ptc}\in\{0,1\} \quad x_{ptc}, s_{pt}, i_{pt}, b_{pt}\in\mathbb{Z}^+ \qquad \forall\, c\in C,\ p\in P, t\in T \tag{6.21}$$

Decision variables i_{pt}, b_{pt}, s_{pt} and z_{ptc} specify the inventory, backlog and delivery volumes, and production lot sizes, respectively, concerning to product p, period t, and cell c. The parameters express the length of periods (t^{w}), customer needs (d_{pt}), setup (t_m^{s}) and processing times (t_m^{c}) of products, and resource requirements where J denotes the set of resource types and r_j^{avail} is the resource pool. In the model, g_{ptc} and y_{ptc} are indicator variables expressing setups and assembly of products with a given resource, and they can be calculated applying a modified version of the *LS-C-B/M1* lot-sizing model by Pochet and Wolsey[3]. The objective function (6.16) minimizes the total costs of backlogs and inventory, while constraints match the production volumes (6.17) with the utilization of modular resources (6.18), with processing times (6.19), and link the consecutive time periods (6.20). Executing the resulting plan with the DES model of the system, the expected future operation and logistics costs can be obtained.

6.1.4 Robust production planning and control method for flexible assembly lines

In production planning concern to flexible, manual assembly lines, the human factor might influence critically the execution of plans. The manual processing times and reject rates of products manifest in varying amount of extra human capacity requirements that can be hardly predicted. These stochastic parameters cannot be handled efficiently even by the latest APS systems, therefore, the execution of calculated plans often leads to latenesses and/or disadvantageous utilization of capacities. In Chapter 5, a new, simulation- and optimization-based robust production planning method was presented that aims at utilizing quasi-real-time data gathered about the system's state to project its future expected behavior applying virtual production scenarios. This projection is performed by the DES model of the system, generating a representative dataset of different production scenarios' capacity requirements —implicitly considering the stochasticity of parameters— to build optimization models upon, and calculate robust production and capacity plans.

[3] Y. Pochet and L. A. Wolsey (2006). *Production planning by mixed integer programming.* Springer.

Thesis 4: The robustness of manually operated flexible assembly lines' production plan can be increased in a proactive way by applying simulation-based optimization. Representing the planning problem with a mixed-integer linear optimization model, the actual human capacity requirements can be expressed with the following function:

$$\boldsymbol{Q\left(\overline{q}_t\right) = \beta_0 + \beta_1 h_t + \sum_{p \in P} \beta_p q_{pt}}$$

The capacity function is obtained by linear regression, where the training dataset for model fitting is provided by a simulation model that represents the quasi-actual state of the assembly line, and executes simulation experiments based on a set of virtual scenarios. In the function, parameters $\boldsymbol{\beta}$ are resulted by regression model fitting, $\boldsymbol{h_t}$ denotes the headcount of operators allocated to the line in period $\boldsymbol{t}$, and $\boldsymbol{q_{pt}}$ defines the assembled volume of product $\boldsymbol{p}$ in period $\boldsymbol{t}$. The application of the function as a constraint in the production planning MIP model guarantees the calculation of robust plans, defining production lot sizes and also corresponding operator headcounts.

The essence of the method relies on a combination of MES and ERP data —that are typically stored and handled separately— and utilizes them in optimization, data analytics and simulation models. In addition to providing input dataset for the regression model fitting, the simulation model also supports the selection of proper capacity control methods, considering various operator headcounts, and stochasticity of the aforementioned planning parameters. According to the experimental results, the model provides robust production plans with reduced lateness, even besides the stochasticity of planning parameters.

6.2 Application of the results

The new methods and models summarized in the previous thesis statements were developed respecting real industrial needs to solve the related emerging practical problems. The validation, testing and evaluation of solutions were primarily done within the *RobustPlaNet: Shock-robust Design of Plants and their Supply Chain Networks*[4] project, in collaboration with industrial partners providing real problem instances, production environment and data (Becker et al., 2016; Egri et al., 2016). The use-cases defined and elaborated within the *RobustPlaNet* and other R&D projects related to the research presented in the thesis mostly concern problems from the automotive industry, however, the methods can be applied in other sectors, as they are not company- but system-specific. Therefore, they are applicable in cases where production environment is composed of flexible and reconfigurable assembly systems that match the specifications provided in the thesis.

The framework presented in Thesis 1-2, and the related models were defined on the basis of more case studies from the automotive industry. The models are not yet applied in everyday practice, however, the framework is applicable to solve real industrial problems, according to the presented results of a comprehensive simulation analysis. They show that proper application of the method results in cost (reconfiguration, operation and space) savings, compared to other analyzed methods. The method presented in Thesis 3 for the lifecycle management of

[4]European Seventh Framework Programme, Grant No. 609087, `http://www.robustplanet.eu`

reconfigurable, robotic assembly cells was tested and validated with a case study provided by *Voestalpine Polynorm B.V.*, located in The Netherlands. According to the results, this method is capable of supporting efficiently the design, management and operation of assembly cells analyzed in the study. Applying the models within the presented workflow, the efforts put in the design of new cells can be reduced significantly, compared to current practice. The robust production planning method presented in Thesis 4 was validated and tested at the plant of *Knorr-Bremse Fékrendszerek Kft.* in Kecskemét, where the models were used to plan the production of a high-runner, flexible, manual assembly line. The obtained results were compared to corporate, norm-time based historical data. Observing these results, one can conclude that the new method provided robust production plans with decreased number of working shifts, increased output volumes and planning flexibility. The list of main R&D projects related to the research presented in the thesis is provided below:

- RobustPlaNet EU FP7 project (2013-2016)
- Knorr-Bremse Benchmark Factory project (2012-2013)
- E.ON network-service planning project (2012-2013)
- Knorr-Bremse SampleShop project (2010-2012)

6.3 Summary and outlook

6.3.1 Summary of the thesis

In the thesis, new production and capacity planning methods were presented, aimed at providing solutions focusing on flexible and reconfigurable systems in the assembly technology. As identified within the literature review, management of product variety is an emergent issue in today's competitive manufacturing, in order to provide the customer-expected service level while managing an increasing variety of products in a cost-efficient way. A key towards achieving this goal is maintaining the internal efficiency by applying proper system structures, and the corresponding planning and control methods to match the order stream with production capacities. Flexible and reconfigurable paradigms exist already for years now, however, especially the latter is gaining more and more attention by the industry recently, thanks to the technology providers offering building blocks and complete modular systems. However, the efficient operation of these systems relies in the application of planning methods that are capable of handling the dynamics of system structure characterized by planning parameters influenced by multiple sources. It was pointed out that costs related to heterogeneous modular assembly systems are also dependent by more features, therefore, the management of these systems asks for novel approaches.

A new, hierarchical framework was proposed to bridge this gap by offering planning methods for modular assembly systems on each level of the classical planning hierarchy. On the strategic level, decisions are taken considering long-term forecasts, and the actual state of the system. These decisions regard investments, and assignment of products to the proper system type on a cost basis. Among those, operational and investment costs are both considered, as they are are highly influenced by medium-term plans calculated on a lower, tactical level. Combining these aspects, the key to solve the strategic level planning problem relies in the proper prediction of operational and investment costs, which task was solved by regression model fitting, applying a set of solutions of tactical level planning model on virtual production scenarios. On both levels of the framework, new planning methods were proposed that are capable of handling the special features of flexible and reconfigurable systems, while providing solutions for real size practical problems applying linear optimization models. Each model of the hierarchy was evaluated with use-case problem instances from the industry, justifying their applicability in real situations.

The framework was defined to manage modular assembly systems that mainly apply manual labor to assemble the products. However, there is also an increasing number of examples from industry for robotic, automated assembly systems. Those systems apply machine resources, mainly due to the joining technology applied to assemble the products. Similarly to the previous case, matching the system's configuration with ever changing product and technology portfolios ask for novel methods to maintain the service level requested by the customers, while achieving cost-efficient operation. As a response to this challenge, a new method was proposed for the design, management and operations of robotic, modular assembly cells, composed of static elements and also modular devices. The method is built up of different tools, of which the *Production Planning and Simulation Tool* is responsible for the dynamic evaluation of new cell configurations, and for the prediction of future expected operational costs already in the early design stage of the system. Integrating this tool in the proposed workflow, it is capable of estimating the production batch sizes by matching the system configuration designed with the previous tools, as well as considering the contractual delivery volumes. In this way, the complete workflow supports system designers and engineers to reduce the efforts put in the design, configuration and reconfiguration of these cells, so as making the management of product variety easier.

The last part of the thesis focused on increasing the robustness of production plans calculated for flexible manual assembly systems, where significant amount of human labor leads to varying planning parameters, due to the human factor. The new proposed method relies on the combination of ERP and MES data in production planning, applying simulation and regression techniques to obtain useful information from lower, process level data, and utilize it in higher level production and capacity planning. The simulation model is applied to analyze the system's behavior, by projecting its quasi-actual state to possible realistic future scenarios. In this way, detailed data about expected capacity requirements can be collected, providing a training set of regression models to build upon. These models are then integrated in production planning models, aimed at defining production lot sizes by considering process-level capacity constraints, and thus providing more robust plans than conventional, norm-time based ones.

6.3.2 Future work and outlook

As summarized in Section 6.3.1, the results presented in the thesis rely on the latest technological advancements in production, considering either modular assembly system structures, as well as complementary information and communication tools supporting the operation of those systems. All the presented methods rely on information that can be obtained about these systems, either considering long-term forecasts, or quasi-real time process level data. This way of utilizing data in production planning methods presents an essential characteristics of I4.0 applications and cyber-physical production systems. The main future direction of the research is also marked by new ways of utilizing data in production planning and control methods. In this perspective, new data analytics tools are in the scope that provide information about key planning and control parameters in almost real-time, implementing a closed-loop of data flow among processes and complementary logical elements. Such advanced applications might not rely on simple regression techniques, but ask for advanced analytics models that enable incremental model training, considering the latest planning data and also historical logs. As a representative example, production in flow-shop systems could be controlled, so as the lead times of individual orders would be predicted on a feature basis, matching with the actual state of the system with other jobs in progress. This kind of advanced data analytics based lead-time prediction and production control not yet exist in industrial practice, however, it has significant relevance as production systems are getting more and more complex, while the amount and detail of available data is ever increasing.

As for the robust production planning and control, the planned future work is twofold. On the one hand (i) an extended analysis of robustness is to be performed, regarding the influence of parameter settings on the planning results and also on the performance indicators when a plan is executed. As discussed in Section 2.5.1, robustness in general have various definitions and interpretations in production planning and control, due to the emerging nature of the field. Therefore, next steps in this direction will involve a broader study of robustness, with an in-depth sensitivity analysis, and a combination of the proposed proactive approach with reactive solutions, to increase the efficiency of plans by recovery methods and performance stabilization if certain conditions demands for that. On the other hand, (ii) the range of considered planning parameters also planned to be broadened, emphasizing especially the natural planning measures like work in progress, delivery performance and resource utilization. Currently, these parameters are only implicitly reflected by the objective function, however, they are of significant importance to measure the effectiveness of operations. Therefore, such parameters will be explicit elements of the objective function, and due to the trade-off relation among them, it will be even more important to perform the aforementioned sensitivity analysis precisely.

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List of abbreviations

APS	advanced planning and scheduling
CMSD	Core Manufacturing Simulation Data
CP	constraint programming
CPS	cyber-physical system
DES	discrete-event simulation
DMS	dedicated manufacturing system
ERP	enterprise resource planning
FMS	flexible manufacturing system
GA	genetic algorithm
KPI	key performance indicator
MLCLSP	multi level capacitated lot-sizing problem
MRP	material requirements planning
MES	manufacturing execution system
OEM	Original Equipment Manufacturer
RMS	reconfigurable manufacturing system
TSP	Travelling Salesman Problem

Nomenclature

Sets	
A	set of assembly operations
C	set of assembly cells
E	set of considered execution modalities
H	set of operator headcounts
J	set of assembly system modules
K	set of product clusters
L	set of "virtual" assembly lines
M	set of components
N	set of customer orders
O	set of operators
P	set of products
T	set of planning time periods
Z	set of different generated configurations
Ω	set of scenarios
Π	set of micro time periods
Parameters	
a_{pc}	compatibility matrix, indicating if product p can be assembled in cell c
c_{nt}	deviation cost of producing order n in period t
c_n^{h}	inventory holding cost of order n
c^{bl}	cost of backlog per product and period
c_n^{l}	lateness cost associated with order n
c_j^{m}	purchase cost of module j
c^{rec}	cost of a reconfiguration
c^{set}	cost of a setup
c^{opr}	average cost of an operator per period
c^{stock}	cost of inventory holding per product and period
c^{opn}	operation cost of a module per time period
c^{chg}	cost of change (assign a product to another system)
c^{dep}	depreciation factor
c^{inv}	investment cost
c^{opc}	operation cost characterizing reconfigurable a cell configuration
c^{tool}	unitary tool cost
d_{pt}	volume of product p to be delivered in t
$d_{m\pi}$	demand volume for component m in micro period π

$f_{p\omega}$	demand for each $p \in p(\omega)$
$h_p^{\max}$	maximum operator headcount of product p
h_n	headcount of operators assigned to task n
$h^{\min}$	minimum headcount of operators working in period t
$j_{p\omega}$	set of production processes for $p \in p(\omega)$
$l_{p\omega}$	batch size for each $p \in p(\omega)$
p_n	product of order n
q_n	order volume associated with order n
r_j^{avail}	number of modules from type j available in the resource pool
r_{jp}	number of modules j required by product p
t_p^{set}	setup time of product p
t_p^{rec}	reconfiguration time of product p
t_p^{proc}	total manual processing time of product p
t_{pa}^{op}	duration of assembly operation a of product p
t^{w}	length of a planning time period
t_n^{d}	production due date of order n
t_{ph}	processing time of product p if assembled by h operators
t_p^{mach}	machine cycle time of product p
t_m^{l}	lead time of component m in the shared resources segment
t_m^{o}	total manual processing time of component m
t_m^{c}	total machine processing time of component m
t_m^{s}	machine setup time of component m
t^{π}	length of a micro time period π
δ	discount rate
$\pi(\omega)$	occurrence probability of a node in the scenario tree
ρ	ratio of the macro and micro periods' length: $t^{\text{w}} = \rho t^{\pi}$ $\rho \in \mathbb{Z}^+$
	Variables
b_{pt}	amount of backlogs from product p in period t
g_{ptc}	setup performed in cell c for product p in period t
h^{total}	total headcount of operators
h_{ct}	headcount of operators working at cell c in period t
i_{pt}	inventory level of product p in period t
n_j	amount of additional modules from type j
q_{pt}	amount of products p produced in period t
$r_{oj\pi}$	assignment of operator o and machine j in micro period π
s_{pt}	amount of product p delivered in period t
t_n^{start}	execution start time of task n
t_n^{end}	execution end time of task n
x_{ptc}	volume of product p assembled in period t and cell c
x_{nt}	execution of order n in period t
y_{ptc}	variable indicating if product p is assembled in period t and cell c
z_{cu}	configuration chosen for cell c in period t
$\omega_{m\pi jo}$	volume of module m machined by operator o in time π on machine j
	Functions
$Q\left(\bar{q}_t\right)$	total manual capacity requirements in period t

β	regression coefficients
Γ	total volume-dependent operation costs
Θ	cost of change
Γ^{s}	volume costs of system s
λ_u^{s}	value of assets in system s and period u
Λ	total invesment costs
Λ_u^{s}	investment costs in system s and period u
Υ	total amount of assembly modules
Φ	total headcount of human operators
Ψ	depreciation costs