



Budapest University of Technology and Economics
Department of Manufacturing Science and Engineering



Hungarian Academy of Sciences
Institute for Computer Science and Control

Production and capacity planning methods for flexible and reconfigurable assembly systems

PhD thesis booklet

Dávid Gyulai

Supervisor:

Prof. László Monostori, academician

Budapest University of Technology and Economics
Department of Manufacturing Science and Technology

Hungarian Academy of Sciences
Institute for Computer Science and Control

Budapest, 2018.

1 Introduction and objectives

1.1 Problem statement and motivation

Producing companies often face the challenges that prediction of customer demands and management of complex product portfolios are harder than ever before, and cost-efficient production requires new, special production and capacity planning methods. In case a company has a diverse product portfolio, most commonly applied, conventional production system structures are not always flexible enough to ensure economical production in the different stages of the products' lifecycle.

My research aimed at developing methods that offer cost-efficient solutions for production and capacity planning problems related to assembly systems, utilizing the advantages of different resource structures (dedicated, flexible, reconfigurable). Real problems from the automotive industry motivated the development of the methods, as characteristics of this sector are the wide product portfolio and fluctuating customer order stream, typically resulted by the *bullwhip effect*. Special features of manual and hybrid assembly systems — that are widely used in the automotive industry — are the flexible adjustment of capacities to meet customer demands, however, changes in the allocated capacities always incur costs that should be minimized, possibly both on short and long terms.

1.2 Objectives of the research

The primary objective of the research was to elaborate capacity planning methods that are capable of harmonizing the production processes with the changing customer demands on the long (strategic), medium (tactical) and short (operational) terms, even in case of a diverse product portfolio. Therefore, such models were analyzed that can provide cost-efficient plans by considering internal (technological), and also external (customer) constraints. The research focused on assembly systems, with the aim of defining a suitable decision support system that enables strategic, tactical and operational level capacity management, and fits into the already existing planning processes.

In the long-term, strategic decisions, the primary task is to determine system (re-)configurations and related investments, based on forecasts that often rely on uncertain data. In addition to the future demands, it is important to consider the actual state of the assembly system, more specifically, the produced goods and the assigned resources. Depending on

production volumes, different system structures provide the most cost-efficient operation: in case the entire assembly system includes dedicated (mass production), flexible (medium batches) and reconfigurable (small batches, or customized production) assembly lines, it has a heterogeneous resource set. The operation and investment costs of resource types depend on several factors that are hard to predict in practice, regarding future scenarios. It is important to highlight that on the long term, investment and operation related costs are in the same order of magnitude, thus both should be considered in decisions related to system configuration. On the strategic level, the objective was to elaborate a new method that supports system configuration by the assignment of products to dedicated, flexible and reconfigurable resources, considering the actual state of the system and the forecast volumes of the products.

On the tactical and operational levels, decision makers have fewer degrees of freedom in capacity management: investment related decisions are strictly constrained, therefore, only existing capacities can be considered in production and capacity planning. In general, the stochasticity of parameters (e.g. manual assembly process times) increases the complexity of production planning, which means a crucial challenge in case of manually operated assembly systems. On the medium term, appropriate planning of human resources is of higher importance than in strategic planning, thus the research was aimed at developing new, robust planning methods that are capable of dealing with human resources efficiently. The key requirement towards the calculated plans is their executability in practice, despite the change of certain parameters (processing times, resource availability etc.). Another requirement—besides robustness—is the ability of models to manage the modular architecture and the frequent reconfigurations of the system.

2 Preliminaries and methodology of the research

2.1 Preliminaries

The management of wide and diverse product portfolios is referred to as *product variety management*, which is one of the greatest challenges in production management, as it influences product design, process and production planning decisions [1]. In order to satisfy customer needs and increase internal, corporate effectiveness, production system structures need to be applied that can be adjusted to the changes in production volumes and in the product

portfolio. Depending on the number of produced variants and their volume, different system types provide the most cost-efficient production: dedicated systems are typically suitable for mass production, while flexible ones are capable of producing a given set of products applying a fix system structure and adjustable technological parameters. Changeable systems gain more application in practice [2], and some types of them have physically changeable system structure, making it possible to adjust them to the products' technological requirements (reconfigurable systems) [3].

Recently, there are numerous companies that manage a wide and diverse product portfolio, and there are significant —sometimes order-of-magnitude— differences among products' volumes. In those cases, production systems with heterogeneous resource structure need to be applied, and the most important task in their strategic system configuration is to assign products to dedicated, flexible or reconfigurable resources and to define the proper amount of resources from each type. Such decisions are made on a cost basis, however, the estimation of investment costs is very challenging, especially if the system's structure changes frequently [4]. In order to solve system configuration related tasks where the objective is to define a heterogeneous resource set, *net present value (NPV)* based methods are often applied as part of the decision making process [5], [6]. However, NPV-based models often limit the flexibility of decision makers, thus they are unable to handle the underlying options of the investment decisions, therefore, *real options* based calculations are more appropriate to solve some of those tasks [7], [8]. In strategic decision, investment cost is usually the only considered factor, nevertheless, it is often in the same order of magnitude with the costs associated with systems' operation, thus the latter cannot be ignored in such decisions. There exist optimization models for system configuration that consider the operation costs of different resource types, however, they are typically suitable for automated manufacturing systems, and cannot be applied for managing modular, reconfigurable assembly systems, due to the difference in system structure and operation mode [9]–[11].

Strategic level capacity management of assembly systems cannot be successful in case the incurring costs are analyzed only from economical perspective [2]. The primary reason for this is the fact that operation costs —that typically incur on tactical and operational levels— and the applied system configuration are in strong relation with technological requirements and processes [12]. The operation costs —incurred on the medium term— are considered primarily in production planning, matching customer demands with resources. So far, only

a few research works considered the medium term production plans, and the costs associated with their execution in strategic planning. The greatest challenge in these tasks is the lack of information about the operation costs, available in the configuration stage of the systems, thus only a few approaches exist that consider the aforementioned factors [13]–[15]. As the structure of modular, fast reconfigurable systems' changes frequently, methods and models need to apply special constraints to solve production planning tasks [16]. This is the main reason for the current lack of fledged system configuration method, which would be capable of efficiently handling operation costs of modular, reconfigurable assembly systems.

Assembly processes often cannot be automated, or it is uneconomical to automate them, thus manual and semi-automated assembly systems are commonly used in industrial practice. In production management of these systems, a great challenge is meant by the deviation of manual processing times, increasing the complexity of capacity planning and line balancing tasks. This is caused by deterministic parameters, considered in system configuration and human workforce planning methods. In case processing times deviate around a mean value, capacity loads become unbalanced making the performance and therefore the output of the entire system uncertain [17]. In relation with manual assembly lines, non-deterministic models are typically elaborated to solve line balancing problems, however, there is no generally applied and accepted method to solve related non-deterministic production and capacity planning problems [18], [19]. In order to handle stochastic processing times in planning appropriately, and manage the resulted load unbalances, robust methods are needed, ensuring that change of the considered parameters within a predefined range will not influence the executability of plans. Even state-of-the-art *advanced planning and scheduling (APS)* systems are unable to calculate such plans [20], therefore, an important objective of the research was to develop robust planning methods that can be applied in industrial practice.

2.2 Research methodology

Within the research, and the solution of the related tasks, an important objective was the application of advanced, state-of-the-art tools and technologies. Digital manufacturing and enterprise solutions provide a wide range of tools, of which appropriate ones were applied in the development of the new methods. Special emphasis was put on the formal definition of the problems and on the solution of the corresponding optimization models, which were mixed-integer linear programs (MIP) in most cases. On strategic and tactical levels, plan-

ning problems were solved by applying declarative mathematical modeling approaches, while on the strategic level, constraint programming tools were also used, as they are typically efficient in solving resource-constrained scheduling problems. The solutions provided by the mathematical models (resource configuration, production plan) were analyzed by a simulated execution in a discrete-event simulation (DES) environment. The greatest strength of DES tools is their ability of supporting detailed, realistic model building even in case of complex system architectures and control logics. Besides, another benefit is the opportunity for considering stochastic parameters and uncertain events (e.g., machine breakdowns), therefore, DES provides an efficient complementary tool for deterministic mathematical models.

State-of-the-art cyber-physical manufacturing and assembly systems provide large amount of technology-related data during operation, moreover, experiments with virtual, simulation and mathematical models also generate useful data that often require advanced analytical tools to obtain useful information. For this reason, data analytics, statistical modeling and learning tools were also applied during the research. The new methods —especially the robust production planning method— rely on production data, collected and processed continuously in order to have models that always represent the actual state of the production system, thus capable of providing reliable results.

3 New scientific results

3.1 Hierarchical capacity management of modular assembly systems

Within the research, a comprehensive framework was presented, offering capacity management solutions for modular, heterogeneous assembly systems on each level of the classical planning hierarchy, even besides a complex product portfolio and changing customer needs (Figure 1). On the highest, strategic level, the long-term system configuration problem was solved to determine the proper product-assembly system assignments and the corresponding investments, 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. Within the framework, strategic level models support investment related decisions, tactical level ones provide solutions for production and capacity planning problems, while the lowest, operational level supports production control decisions. The vertical

integration of decisions is guaranteed in the framework, as solutions calculated on higher levels provide input for lower level decisions.

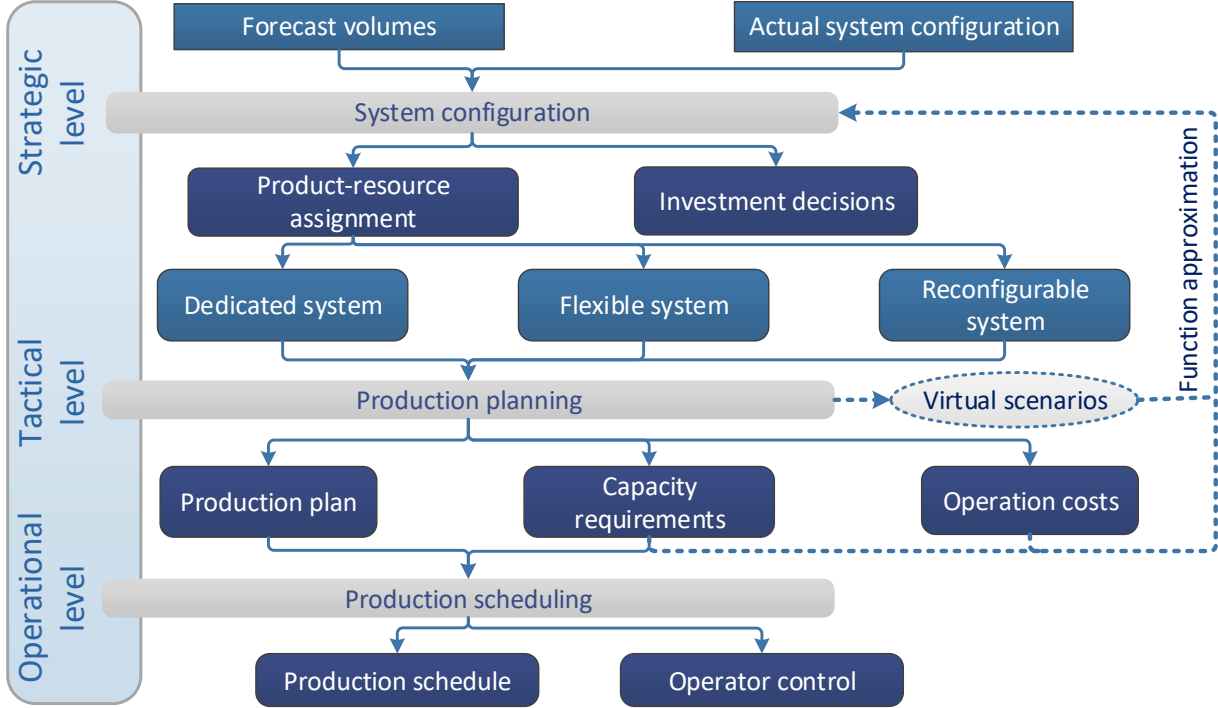


Figure 1: Hierarchical capacity management framework for modular assembly systems.

3.1.1 Strategic level system configuration and product-resource assignment

Regarding modular assembly systems with a heterogeneous resource set, the most important strategic decisions relate to the assignment of products to different resources. The key question on the long term (the horizon is typically some months or years long) is whether to assemble a product with dedicated, flexible or reconfigurable resources. The objective of decisions is to minimize the long-term costs, taking into account the future expected customer needs, and also the available resource sets. Such product-resource assignment decisions typically involve investments, therefore, an emerging system configuration problem is also to be solved in parallel to guarantee that available capacities will always match the customer-expected production rates. In this regard, two main types of strategic decisions are distinguished: product-based and portfolio-based ones.

In *product-based* decisions, the objective is to minimize the costs by identifying the resource type, which results in the lowest production and investment costs if a product is

assigned to it. The greatest challenge in these cases is to predict accurately the operation costs of reconfigurable resources, as they apply a common, shared resource pool to build up the assembly lines, therefore, the costs are nonlinear functions of production volumes, and key performance indicators are influenced by the applied planning policy [C1]. New, product-based decision support methods were developed within the research, applying regression methods—built upon the results of experiments with simulation and optimization models—to approximate the nonlinear cost functions. These methods supported the solution of a so-called line-assignment problem, answering the question: which products need to be assembled with dedicated and reconfigurable resources, and which ones' production need to be outsourced. The achieved results of product-based decisions proved that it is possible to approximate the costs—incurring on the tactical level—related to the reconfigurable system by applying multivariate linear regression models.

Accordingly, a new *portfolio-based* decision support method was developed within the research, providing solutions for both resource assignment and system configuration problems. The method considers the relations among different products' assembly processes, which are important especially in reconfigurable systems, due to the use of a common resource pool by several products. As a solution of the problem, I proposed a new, integer optimization model, in which various operation- and investment-related costs are approximated by regression models, and the training dataset of regression is provided by solutions of the tactical level planning problem, using virtual scenarios. In this way, operation and investment costs can be efficiently predicted, considering both the applied system configuration and the related capacity requirements, in case of all resource types. In order to handle the nonlinear relations among different products' assembly processes, new variables are introduced in the model, while keeping its linearity which is important from mathematical viewpoint.

Thesis 1: In the capacity management framework of modular assembly 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

$$\Psi(z_{pu}^s, w_{pu}^s) + \Theta(z_{pu}^s, w_{pu}^s) + \Gamma(z_{pu}^s, w_{pu}^s) + \Lambda(z_{pu}^s, g_{bu}^s) \quad (1)$$

subject to

$$\sum_{s \in S} z_{pu}^s = 1 \quad \forall p \in P, u \in U \quad (2)$$

$$w_{pu}^s \geq z_{pu}^s - z_{p,u-1}^s \quad \forall p \in P \quad (3)$$

$$g_{bu}^s \geq z_{pu}^s \quad \forall b \in B = \{1 \dots p_b\} \quad (4)$$

$$\Phi(z_{pu}^s) \leq h^{\max} \quad \forall p \in P, u \in U, s \in S \quad (5)$$

$$\Upsilon(z_{pu}^s) \leq m^{\max} \quad \forall p \in P, u \in U, s \in S \quad (6)$$

$$z_{pu}^s \in \{0, 1\} \quad w_{pu}^s \in \{0, 1\} \quad g_{bu}^s \in \{0, 1\} \quad \forall p \in P, u \in U, s \in S, b \in B \quad (7)$$

In the objective function (1), Ψ , Θ , Λ and Γ express depreciation, change of assignment, investment and operation costs, respectively. Constraints (2)-(4) guarantee the feasibility of the solution, while (5) and (6) are technological constraints, bounding the utilization of human (5) and machine (6) resources. The nonlinear Ψ , Θ , Λ and Γ 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_{pu}^s specifies if product p in period u is assembled in system s , and g_{bu}^s expresses if all elements of an arbitrarily chosen subset b of products are assembled in system s in period u .

The results summarized in Thesis 1 are discussed in Chapter 3, and the publications related to the thesis are the following: [J1],[J2],[C2],[C3],[C1],[C4],[O1]

3.1.2 Tactical level production and capacity planning

In case of the analyzed modular assembly system with heterogeneous resource set, the objective of medium-term planning decisions is to determine production lot sizes, based on the customer orders and available internal capacities. While fledged planning methods already

exist for dedicated and flexible resources, there is no available, published method which supports production and capacity planning of modular, fast-reconfigurable assembly systems. Within the research, I worked out new integer programming models that provide solutions for tactical level planning problems, moreover, they can be generally applied to support higher level strategic, and also lower level operative decisions, considering dedicated, flexible and also reconfigurable resources. Applying the models on virtual scenarios, the training set of regression models can be obtained, to approximate cost functions that are important in strategic decisions. In this case, the planning model needs to apply modified constraints and objective function to enable investments in new resources. In order to minimize the number of physical system reconfigurations, two main options exist: either applying new constraints and indicator variables, or capturing this sub-problem as a traveling salesman problem (TSP). In the latter case, it is supposed that only a single product type is produced with a given line in a given time period (small bucket model).

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

$$\sum_{t \in T} c^{\text{opr}} h_t + \sum_{p \in P} \sum_{t \in T} c^{\text{set}} y_{pt} + \sum_{t \in T} \sum_{n \in N} c_{nt} x_{nt} + \sum_{t \in T} \sum_{n \in N} \sum_{j \in J} c^{\text{opn}} x_{nt} r_{jp_n} \quad (8)$$

subject to

$$\sum_{t \in T} x_{nt} = 1 \quad \forall n \in N \quad (9)$$

$$n_j \leq r_j^{\text{avail}} \quad \forall j \in J \quad (10)$$

$$\sum_{p \in P} r_{jp} y_{pt} \leq n_j \quad \forall j \in J, t \in T \quad (11)$$

$$x_{nt} \leq y_{pt} \quad \forall t \in T, p = p_n, n \in N \quad (12)$$

$$\sum_{n \in N} x_{nt} t_p^{\text{proc}} + y_{pt} (t_p^{\text{rec}} + t_p^{\text{set}}) \leq h_t t^w \quad \forall t \in T, p = p_n \quad (13)$$

$$h_t \in \mathbb{Z}^+ \quad n_j \in \mathbb{Z}^+ \quad y_{pt} \in \mathbb{Z}^+ \quad x_{nt} \in \{0, 1\} \quad \forall j \in J, t \in T, n \in N, p = p_n \quad (14)$$

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 (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 (9), module consumption (10-11), setups (12) and operator headcount (13). Introducing an additional element $\sum_{j \in J} n_j c_j^{\text{m}}$ 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 (11) needs to be disregarded.

$$\sum_{t \in T} c^{\text{opr}} h_t + \sum_{p \in P} \sum_{t \in T} c^{\text{set}} y_{pt} + \sum_{t \in T} \sum_{n \in N} c_{nt} x_{nt} + \sum_{t \in T} \sum_{n \in N} \sum_{j \in J} c^{\text{opn}} x_{nt} r_{jp_n} + \sum_{j \in J} c_j^{\text{m}} n_j \quad (15)$$

Slightly modifying the decision variables in the above formulation, a new model can be obtained that specifies the production lot sizes, and also 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.

In case the planning problem is formulated with 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 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 TSP's solution is a time-indexed plan, specifying production lot sizes and the corresponding resource usage. The results summarized in Thesis 2 are discussed in Chapter 3, and the publications related to the thesis are the following: [J1],[J2],[C2],[C3],[C1],[C4],[C5],[O1]

3.2 Capacity management of modular, robotic assembly cells

Similarly to manually operated reconfigurable assembly systems, modularization of automated, robotic assembly cells is also possible, increasing the adaptability of these systems to changing production volumes and increasing number of product types. Such assembly cells are still rarely used in industrial practice, however, they are considered as efficient and innovative solutions, mainly for automotive supplier companies that often face the challenges of OEM-requested short response times, management of wide product portfolios and corresponding wide portfolios of assembly technologies. Within the research, I investigated robotized car body assembly cells, composed of fix, static components (e.g. a robot installed on a conveyor track) and also mobile, changeable (*plug-and-produce*) technological modules (e.g., a welding or gluing station).

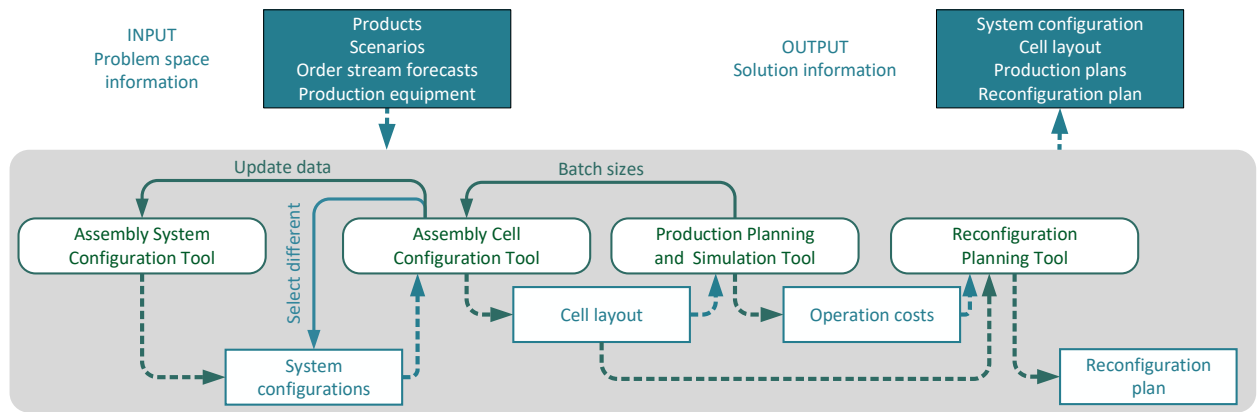


Figure 2: Design and management framework for modular assembly cells.

A new, mathematical programming- and simulation-based method —called *Production Planning and Simulation Tool*— was developed that can be applied already in the early design stage of modular robotic assembly cells to predict their expected future operation costs, thus making the cost-optimal cell configuration and lifecycle management possible. The method is part of a decision-support workflow —illustrated by Figure 2— that supports the (i) rough design of cells (*Assembly System Configuration Tool*), and also their (ii) detailed configuration (*Assembly Cell Configuration Tool*). The (iii) third step of the workflow is the prediction and calculation of different configurations’ operation costs, taking into account forecast- and contract-based order batch sizes. The method is completed by a (iv) stochastic programming model in the *Reconfiguration Planning Tool*, performing the optimization of the cell configuration on a long-term, discrete time horizon considering technological constraints,

and also investment, operation and reconfiguration costs determined by the previous tools.

The method and the decision support workflow presented in the thesis are results of a collaborative work: parts (i)¹, (ii) and (iv)² are works of other academic partners, while the development of part (iii) and its integration in the workflow are own scientific results.

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 lot sizes can be calculated with the following model:

minimize

$$\sum_{p \in P} \sum_{t \in T} (c^{\text{bl}} b_{pt} + c^{\text{stock}} i_{pt}) \quad (16)$$

subject to

$$s_{pt} \geq d_{pt} \quad \forall p \in P, t \in T \quad (17)$$

$$\sum_{c \in C} \sum_{p \in P} r_{jp} y_{ptc} \leq r_j^{\text{avail}} \quad \forall t \in T, j \in J \quad (18)$$

$$\sum_{p \in P} (t_m^c x_{ptc} + t_m^s g_{ptc}) \leq t^w \quad \forall c \in C, t \in T \quad (19)$$

$$i_{pt} - b_{pt} = i_{p,t-1} - b_{p,t-1} - s_{pt} + \sum_{c \in C} x_{ptc} \quad \forall p \in P, t \in T \quad (20)$$

$$g_{ptc}, y_{ptc} \in \{0, 1\} \quad x_{ptc}, s_{pt}, i_{pt}, b_{pt} \in \mathbb{Z}^+ \quad \forall c \in C, p \in P, t \in T \quad (21)$$

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 Wolsey³. The

¹(i): Johannes Unglert, Juan Manuel Jauregui Becker (Universiteit Twente, Hollandia)

²(ii) and (iv): Massimo Manzini, Marcello Urgo, Marcello Colledani (Politecnico di Milano, Olaszország)

³Y. Pochet and L. A. Wolsey, *Production planning by mixed integer programming*. Springer, 2006.

objective function (16) minimizes the total costs of backlogs and inventory, while constraints match the production volumes (17) with the utilization of modular resources (18), with processing times (19), and link the consecutive time periods (20). Executing the resulting plan with the DES model of the system, the expected future operation and logistics costs can be obtained.

In addition to the refinement of operation costs considered in steps (i) and (ii), the *Production Planning and Simulation Tool* provides feedback for the (ii) *Assembly Cell Configuration Tool* about the expected, realistic production batch sizes, refining a calculated system configuration accordingly. Through the application results of the method in a case study, I proved that it can be applied successfully for production planning of modular, robotic assembly cells that are composed of static parts and changeable technological modules. The method takes into account commonly used, shared resource pools, considering assembly technological constraints.

The results summarized in Thesis 3 are discussed in Chapter 4, and the publications related to the thesis are the following: [J3], [J4],[C6],[C7]

3.3 Robust production planning and control method for flexible assembly lines

It is often faced in industrial practice that uncertainties are introduced in the execution of short-term production plans by the *human factor*, as a side-effect of the allocated manpower in manually operated flexible assembly lines. Varying manual processing times and the reject rates of products lead to additional capacity requirements, however, their amount can be hardly predicted due to their stochastic nature. Such parameters cannot be handled efficiently even by the latest APS⁴ systems, therefore, the execution of plans is often accompanied by lateness and/or unbalanced resource utilizations. Within the research, a new, simulation- and optimization-based robust production planning method was developed that aims at utilizing quasi-real-time data gathered about the system's state to project its expected future 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, which are capable of calculating production and capacity plans (Figure 3).

⁴Advanced planning and scheduling

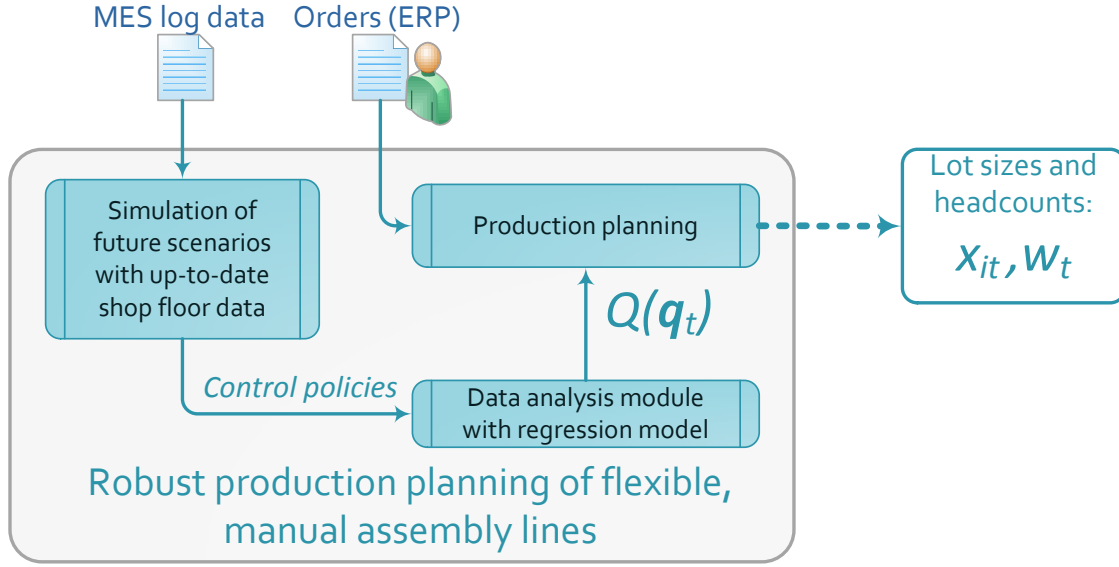


Figure 3: Robust production planning and control method.

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:

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

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 β are resulted by regression model fitting, h_t denotes the headcount of operators allocated to the line in period t , and q_{pt} defines the assembled volume of product p in period 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 MES⁵ and ERP⁶ data —typically stored and handled separately— which are utilized in optimization, data analytics and sim-

⁵Manufacturing execution system

⁶Enterprise resource planning

ulation 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 stochasticity of the considered planning parameters.

The results summarized in Thesis 4 are discussed in Chapter 5, and the publications related to the thesis are the following: [J5],[C3],[C7],[C8],[C9],[C10],[C11], [O2]

4 Application of the methods in practice

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 the solutions were primarily done within the *RobustPlaNet: Shock-robust Design of Plants and their Supply Chain Networks*⁷ project, in collaboration with industrial partners providing real problem instances, production environment and data [C7], [O2]. The use-cases —defined and elaborated within the *RobustPlaNet* and other R&D projects— related to the research and presented in the thesis mostly concern problems from the automotive industry, however, the methods can be applied in other sectors as well, 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 Theses 1-2, and the related models were defined on the basis of several 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 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

⁷European Seventh Framework Programme, Grant No. 609087, <http://www.robustplanet.eu>

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 the 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)

5 Bibliography

5.1 References

- [1] H. A. ElMaraghy, G. Schuh, W. ElMaraghy, F. Piller, P. Schönsleben, M. Tseng, and A. Bernard, “Product variety management”, *CIRP Annals-Manufacturing Technology*, vol. 62, no. 2, pp. 629–652, 2013.
- [2] H.-P. Wiendahl, H. A. ElMaraghy, P. Nyhuis, M. F. Zäh, H.-H. Wiendahl, N. Duffie, and M. Brieke, “Changeable manufacturing-classification, design and operation”, *CIRP Annals-Manufacturing Technology*, vol. 56, no. 2, pp. 783–809, 2007.
- [3] M. G. Mehrabi, A. G. Ulsoy, and Y. Koren, “Reconfigurable manufacturing systems: Key to future manufacturing”, *Journal of intelligent manufacturing*, vol. 11, no. 4, pp. 403–419, 2000.
- [4] Y. Koren, “General RMS characteristics. comparison with dedicated and flexible systems”, in *Reconfigurable manufacturing systems and transformable factories*, Springer, 2006, pp. 27–45.
- [5] O. Kuzgunkaya and H. ElMaraghy, “Economic and strategic perspectives on investing in RMS and FMS”, *International Journal of Flexible Manufacturing Systems*, vol. 19, no. 3, pp. 217–246, 2007.

- [6] D. A. Elkins, N. Huang, and J. M. Alden, “Agile manufacturing systems in the automotive industry”, *International Journal of Production Economics*, vol. 91, no. 3, pp. 201–214, 2004.
- [7] M. Amico, F. Asl, Z. Pasek, and G. Perrone, “Real options: An application to RMS investment evaluation”, in *Reconfigurable manufacturing systems and transformable factories*, A. I. Dashchenko, Ed., Springer, 2006, pp. 675–693.
- [8] J. Milberg and N. Möller, “Valuation of changeable production systems”, *Production Engineering*, vol. 2, no. 4, pp. 417–424, 2008.
- [9] I. Niroomand, O. Kuzgunkaya, and A. A. Bulgak, “Impact of reconfiguration characteristics for capacity investment strategies in manufacturing systems”, *International Journal of Production Economics*, vol. 139, no. 1, pp. 288–301, 2012.
- [10] I. Niroomand, O. Kuzgunkaya, and A. A. Bulgak, “The effect of system configuration and ramp-up time on manufacturing system acquisition under uncertain demand”, *Computers & Industrial Engineering*, vol. 73, pp. 61–74, 2014.
- [11] W. Wang and Y. Koren, “Scalability planning for reconfigurable manufacturing systems”, *Journal of Manufacturing Systems*, vol. 31, no. 2, pp. 83–91, 2012.
- [12] S. J. Hu, J. Ko, L. Weyand, H. A. ElMaraghy, T. Lien, Y. Koren, H. Bley, G. Chrysosouris, N. Nasr, and M. Shpitalni, “Assembly system design and operations for product variety”, *CIRP Annals-Manufacturing Technology*, vol. 60, no. 2, pp. 715–733, 2011.
- [13] E. Nazarian, J. Ko, and H. Wang, “Design of multi-product manufacturing lines with the consideration of product change dependent inter-task times, reduced changeover and machine flexibility”, *Journal of Manufacturing Systems*, vol. 29, no. 1, pp. 35–46, 2010.
- [14] N. Boysen, M. Flidner, and A. Scholl, “A classification of assembly line balancing problems”, *European Journal of Operational Research*, vol. 183, no. 2, pp. 674–693, 2007.
- [15] D. Battini, M. Faccio, A. Persona, and F. Sgarbossa, “New methodological framework to improve productivity and ergonomics in assembly system design”, *International Journal of Industrial Ergonomics*, vol. 41, no. 1, pp. 30–42, 2011.

- [16] M. Abbasi and M. Houshmand, “Production planning and performance optimization of reconfigurable manufacturing systems using genetic algorithm”, *The International Journal of Advanced Manufacturing Technology*, vol. 54, no. 1-4, pp. 373–392, 2011.
- [17] H. Aytug, M. A. Lawley, K. McKay, S. Mohan, and R. Uzsoy, “Executing production schedules in the face of uncertainties: A review and some future directions”, *European Journal of Operational Research*, vol. 161, no. 1, pp. 86–110, 2005.
- [18] M. F. F. Rashid, W. Hutabarat, and A. Tiwari, “A review on assembly sequence planning and assembly line balancing optimisation using soft computing approaches”, *The International Journal of Advanced Manufacturing Technology*, vol. 59, no. 1-4, pp. 335–349, 2012.
- [19] U. Özcan, “Balancing stochastic two-sided assembly lines: A chance-constrained, piecewise-linear, mixed integer program and a simulated annealing algorithm”, *European Journal of Operational Research*, vol. 205, no. 1, pp. 81–97, 2010.
- [20] P. Genin, A. Thomas, and S. Lamouri, “How to manage robust tactical planning with an APS (advanced planning systems)”, *Journal of Intelligent Manufacturing*, vol. 18, no. 2, pp. 209–221, 2007.

5.2 Own publications related to the thesis statements

Journal papers (*Web of Science*)

- [J1] D. Gyulai and L. Monostori, “Capacity management of modular assembly systems”, *Journal of Manufacturing Systems*, vol. 43, no. 1, pp. 88–99, 2017, **IF: 2.77**. DOI: 10.1016/j.jmsy.2017.02.008.
- [J2] D. Gyulai, B. Kádár, A. Kovács, and L. Monostori, “Capacity management for assembly systems with dedicated and reconfigurable resources”, *CIRP Annals – Manufacturing Technology*, vol. 63, no. 1, pp. 457–460, 2014, **IF: 2.25**. DOI: 10.1016/j.cirp.2014.03.110.
- [J3] M. Manzini, J. Unglert, D. Gyulai, M. Colledani, J. M. Jauregui Becker, L. Monostori, and M. Urgo, “An integrated framework for design, management and operation of reconfigurable assembly systems”, *Omega - The International Journal of Management Science*, 2017, Special issue: Customized Assembly Systems (In Print), **IF: 4.02**, ISSN: 0305-0483. DOI: 10.1016/j.omega.2017.08.008.

- [J4] M. Colledani, D. Gyulai, L. Monostori, M. Urgo, J. Unglert, and F. Van Houten, “Design and management of reconfigurable assembly lines in the automotive industry”, *CIRP Annals-Manufacturing Technology*, vol. 65, no. 1, pp. 441–446, 2016, **IF: 2.54**. DOI: 10.1016/j.cirp.2016.04.123.
- [J5] D. Gyulai, A. Pfeiffer, and L. Monostori, “Robust production planning and control for multi-stage systems with flexible final assembly lines”, *International Journal of Production Research*, vol. 55, no. 13, pp. 3657–3673, 2017, **IF: 2.32**. DOI: 10.1080/00207543.2016.1198506.

International conference papers

- [C1] D. Gyulai, Z. Vén, A. Pfeiffer, J. Váncza, and L. Monostori, “Matching demand and system structure in reconfigurable assembly systems”, *Procedia CIRP*, vol. 3, pp. 579–584, 2012, *45th CIRP Conference on Manufacturing Systems–CIRP CMS 2012, Athens, Greece*. DOI: 10.1016/j.procir.2012.07.099.
- [C2] D. Gyulai, B. Kádár, and L. Monostori, “Capacity planning and resource allocation in assembly systems consisting of dedicated and reconfigurable lines”, *Procedia CIRP*, vol. 25, pp. 185–191, 2014, *8th International Conference on Digital Enterprise Technology–CIRP DET 2014, Stuttgart, Germany*. DOI: 10.1016/j.procir.2014.10.028.
- [C3] D. Gyulai, “Novel capacity planning methods for flexible and reconfigurable assembly systems”, in *4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications – SIMULTECH*, SCITEPRESS, 2014. [Online]. Available: <http://eprints.sztaki.hu/8142>.
- [C4] D. Gyulai and Z. Vén, “Order-stream-oriented system design for reconfigurable assembly systems”, in *Proceedings of the Factory Automation 2012 Conference*, University of Pannonia, 2012, pp. 138–143. [Online]. Available: <http://eprints.sztaki.hu/id/eprint/7374>.
- [C5] D. Gyulai, B. Kádár, and L. Monostori, “Scheduling and operator control in reconfigurable assembly systems”, *Procedia CIRP*, vol. 63, pp. 459–464, 2017, *50th CIRP Conference on Manufacturing Systems – CIRP CMS 2017, Taichung City, Taiwan*. DOI: 10.1016/j.procir.2017.03.082.

- [C6] D. Gyulai, A. Pfeiffer, B. Kádár, and L. Monostori, “Simulation-based production planning and execution control for reconfigurable assembly cells”, *Procedia CIRP*, vol. 57, pp. 445–450, 2016, *49th CIRP Conference on Manufacturing Systems–CIRP CMS 2016, Stuttgart, Germany*. DOI: 10.1016/j.procir.2016.11.077.
- [C7] J. M. J. Becker, B. Kádár, M. Colledani, N. Stricker, M. Urgo, J. Unglert, D. Gyulai, and E. Moser, “The robustplanet project: Towards shock-robust design of plants and their supply chain networks”, *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 29–34, 2016. DOI: 10.1016/j.ifacol.2016.07.545.
- [C8] D. Gyulai, B. Kádár, and L. Monostori, “Robust production planning and capacity control for flexible assembly lines”, in *Proceedings of the 15th IFAC/IEEE/IFIP/IFORS Symposium, Information Control Problems in Manufacturing, Ottawa, Canada*, IFAC, 2015, pp. 2380–2385. DOI: 10.1016/j.ifacol.2015.06.432.
- [C9] D. Gyulai and L. Monostori, “Capacity analysis and planning for flexible assembly lines”, in *Proceedings of International Automation Congress 2014*, MATE, 2014, pp. 38–47. [Online]. Available: <http://eprints.sztaki.hu/id/eprint/8086>.
- [C10] A. Pfeiffer, D. Gyulai, B. Kádár, and L. Monostori, “Manufacturing lead time estimation with the combination of simulation and statistical learning methods”, *Procedia CIRP*, vol. 41, pp. 75–80, 2016. DOI: 10.1016/j.procir.2015.12.018.
- [C11] A. Pfeiffer, D. Gyulai, and L. Monostori, “Improving the accuracy of cycle time estimation for simulation in volatile manufacturing execution environments”, in *Proceedings of ASIM Simulation in Production and Logistics 2017 conference, ASIM Simulation in Production and Logistics 2017, Kassel, Germany*, ASIM, 2017, pp. 177–186.

Short papers and papers in Hungarian

- [O1] D. Gyulai, “Bilevel capacity management with reconfigurable and dedicated resources”, in *XIX. International Scientific Conference of Young Engineers, In Hungarian*, EME, 2014. [Online]. Available: <http://eda.eme.ro/handle/10598/28228>.
- [O2] P. Egri, D. Gyulai, B. Kádár, and L. Monostori, “Production planning on supply network and plant levels: The RobustPlaNet approach”, *ERCIM (European Research Consortium for Informatics & Mathematics) News*, no. 105, pp. 14–15, 2016. [Online]. Available: <http://eprints.sztaki.hu/id/eprint/8901>.