Capacity management of modular assembly systems

Dávid Gyulai[a,b,*], László Monostori[a,b]

[a] Fraunhofer PMI at Institute of Computer Science and Control, Hungarian Academy of Sciences, Kende 13-17, H-1111 Budapest, Hungary
[b] Budapest University of Technology and Economics, Müegyetem rkp. 3. T/4, H-1111 Budapest, Hungary

Abstract

Companies handling large product portfolio often face challenges that stem from market dynamics. Therefore, in production management, efficient planning approaches are required that are able to cope with the variability of the order stream to maintain the desired rate of production. Modular assembly systems offer a flexible approach to react to these changes, however, there is no all-encompassing methodology yet to support long and medium term capacity management of these systems. The paper introduces a novel method for the management of product variety in assembly systems, by applying a new conceptual framework that supports the periodic revision of the capacity allocation and determines the proper system configuration. The framework has a hierarchical structure to support the capacity and production planning of the modular assembly systems both on the long and medium term horizons. On the higher level, a system configuration problem is solved to assign the product families to dedicated, flexible or reconfigurable resources, considering the uncertainty of the demand volumes. The lower level in the hierarchy ensures the cost optimal production planning of the system by optimizing the lot sizes as well as the required number of resources. The efficiency of the proposed methodology is demonstrated through the results of an industrial case study from the automotive sector.

Keywords: modular assembly system, reconfiguration, capacity management, production planning

*Corresponding author
Email address: david.gyulai@sztaki.mta.hu (Dávid Gyulai)

1. Introduction and motivation

A recent trend in production management is that companies are pushed by competitive markets and by facing several challenges arising from the management of a great variety of products with shortening life-cycles and customer-expected lead times. These requirements have significant impacts on the applied production technology: the production systems have to follow the trends of the products' life-cycle in order to maintain the economies of scale meaning the balance between the expected throughput and the corresponding production costs. 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 [1]. Furthermore, economies of scope also have to be reached by the proper management of the product portfolio with respect to three main activities: design, planning and manufacturing [2].

Focusing on assembly systems, the above mentioned important business goals can be achieved by utilizing the modularity of the products as well as the flexibility of the applied assembly systems [3]. This can be done by reducing the variant-dependent components in the systems, and applying systems that are built up of universal modules [4]. 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 [5]. The advantages of these systems can be utilized only if the right balance among the different capacities is found. Considering the design of modular assembly systems, an important task is to find the most appropriate system configuration that provides the desired production rate on the lowest possible cost [6]. Besides the proper physical structure of the applied system, there is an obvious need for the efficient production planning and control that supports the application of flexible and reconfigurable systems [7]. In case of assembly technology, the system configuration and production planning processes strongly rely on each other, therefore, they are often combined in a common methodology [8].

The paper introduces a novel method 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 framework has a hierarchical structure to support the capacity and production planning of modular assembly systems, both on a longer and shorter time horizons. 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 optimal production planning of the system by optimizing the lot sizes as well as the required number of modules. An important open question of this field is the consideration and prediction of the future-realized costs, characterizing the investments and operation of a certain system configuration. The substantial contribution and novelty of the paper 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 additional decision variables (product subsets are determined with statistical models), keeping the linearity of the models while capturing the underlying interactions among the processes. This results in a production management framework with ongoing reconfiguration decisions at both strategic and tactical levels, enabling the minimization of the overall costs, relating to production and investments.

The structure of the paper is as follows. In Section 2, a literature review is provided, summarizing the state-of-the-art of modular system and the related capacity management methods. In Section 3, the production environment —considered in the paper— is described, highlighting the operation of the systems with the related costs and decisions. Section 4 provides a problem statement with the respected objectives, decisions and constraints. Section 5 introduces the proposed solution with the description of the hierarchical decision framework and its elements. Then, a real industrial case study is provided to evaluate the efficiency of the proposed methodology, compared different, most commonly applied rule-based solutions.

2. Literature review

Considering large product portfolios, the efficient management of assembly systems is a crucial financial issue, as product lifecycles are shortening, the number of variants is growing and traditional assembly systems are composed of variant-dependent components, thus they are usually unable to adapt to the changes cost-efficiently [9, 4, 10]. Therefore, the application of flexible and reconfigurable assembly systems should be considered, in order to achieve the economy of scale [11]. According to Wiendahl et al., flexibility and reconfigurability are specific to certain factory levels, therefore the term changeability is introduced as an umbrella concept that encompasses many aspects of change within an enterprise [12].

2.1. Comparison of dedicated, flexible and reconfigurable resources

Production technology has three main paradigms regarding the structure, management, and focus of the applied resources: dedicated (DMS), flexible (FMS), and reconfigurable manufacturing systems (RMS) [13]. There are no definite boundaries and specifications that categorize the above systems, however, dedicated systems are usually characterized by lower investment and higher changing costs, whereas flexible systems have the opposite characteristics [14]. Reconfigurable systems are in between them by offering a reasonable solution with relatively lower investment and changing costs. In the paper, a comprehensive capacity management approach is proposed, focusing on modular assembly systems. These systems consist of modular assembly lines that are designed to perform sequential assembly operations. The structure of the lines rely on the process-based alignment of assembly modules. Based on the structure of the modules, one can distinguish among dedicated, flexible and reconfigurable assembly lines. In order to characterize the different types of modules, some important concepts have to be clarified first, concerning the structure and operation of the system:

- *Modules* are the building blocks of modular assembly systems that are capable of performing specific types assembly tasks (e.g. screwing station, pressing station etc.). From structural point of view, one can distinguish among dedicated, flexible and reconfigurable modules from each types. Modular design is a commonly applied technique for assembly systems, since it enables to build different system configuration from blocks with standardized features (often referred as *"plug and produce"* modules [12, 15]).

- *System configuration* refers to the design, selection and alignment of the system elements (e.g. modules). Given a certain product, more configuration alternatives exist that are capable of producing the product. Therefore, different performance measures need to be considered when selecting a system configuration: investment cost, quality, throughput, scalability and conversion time.

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

Dedicated, flexible and reconfigurable paradigms have advantages and disadvantages, therefore, the application of the different assembly lines is a crucial point when discussing the efficiency and economy of the assembly system. Several papers compare the three paradigms of production systems, however, the rest of them concentrate mostly on manufacturing processes [16, 17, 4]. Some of the characteristics summarized in the papers are valid for assembly systems as well, however, they have some specific features. Therefore, a brief introduction of the three types of assembly systems is provided.

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 entails 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 on a screwdriver and the torque range). 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 line is 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 combination of the flexible and reconfigurable paradigms, 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 [12].

Reconfigurable assembly lines are capable of producing more product families, by applying changeable fixtures and adjustable equipment. The modular structure enables to change the configuration of the system with relatively low effort, and scale up or down the capacity according to the order stream.

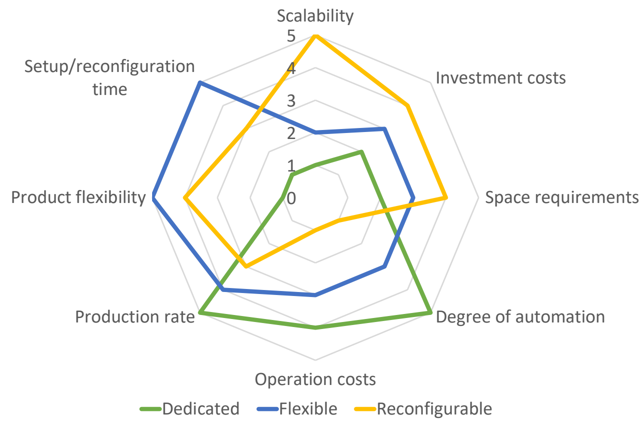

Figure 1: Radar chart with the features of different assembly system types

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 [18, 19]. Utilizing these features, reconfigurable lines are usually applied for assembling products in the launch and end phases of their lifecycle [20]. Based on the above characterization and literature review, a radar chart is sketched by the authors to visualize the main features of the different resource types, higher scores correspond to more advantageous characteristics (Fig. 1). As introduced in the following sections, a system configuration is aimed to be determined, which combines the advantages of the three separate system types mentioned above. Concerning Fig. 1 this would mean that the desired combined system configuration needs to maximize the intersection area presented in the chart.

2.2. Capacity management of assembly systems

In operations management, the general task is to match supply with demand while minimizing the total incurring production costs. When considering several products and dynamic market environment, this can be achieved by utilizing the flexibility and reconfigurability of the applied production resources. In this paper, a comprehensive decision support methodology is defined that aims at minimizing cost functions both on the tactical and strategic levels.

Supplier companies, especially in the automotive industry, often face the challenge to introduce new product in their portfolio, because their customers also release new final products or modify the existing ones, requiring the modification of the components. As markets are usually 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 balance between throughput and production costs, e.g. by applying flexible and reconfigurable resources [7]. In this way, the adaptability of the system to the changing product portfolio can be increased, while the total incurring costs can be kept on a reasonable level.

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 incur on the long run, while keeping the desired service level [21]. In the terminology, this field of corporate decisions is also referred to as resource investment strategy [22]. For manufacturing systems composed of flexible, reconfigurable and dedicated machines, an optimization model was introduced in [14], in order to minimize the production costs by optimally investing in the different machine types. More approaches exist applying search metaheuristics to identify the proper configuration of manufacturing systems, consisting of dedicated, flexible and reconfigurable resources [23, 24, 25], while in [26], an agent-based solution is proposed to manage capacity exchange among production lines combining different resource types. When discussing the production planning and control level of the changeable systems, five important enablers have to be considered: modularity, scalability, neutrality, adjustability and compatibility. In the paper, the first two terms are highlighted: the system itself is composed of modules providing the scalability of the system as a whole [12]. 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 [27]. To identify the best capacity scaling policies of reconfigurable systems, system dynamics [28, 29], dynamic optimization [30], and also genetic algorithm [31, 32] based methods are proposed.

Although various methods exist to manage production systems composed of different resource types, financial and 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 [33]. The reason for this is the specialty of the production environment with lightweight assembly stations enabling rapid reconfigurations, while the above introduced methods regard mostly long term reconfigurations, or modular manufacturing systems with heavy machines and tools. 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, and assigning them to reconfigurable/flexible and dedicated resources respectively, without any optimization (to be discussed in detail in Section 6). Moreover, the production planning and the related operational costs are not considered by practical and theoretical production management approaches, often resulting in wrong investment decisions [34].

3. 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. In order to visualize the main general characteristics of the system, charts of numerical analysis are provided (Fig. 2-4) that relate to the case study introduced in Section 6.

3.1. System structure

Important characteristics of the considered problem is the modularization of the 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 clusters are formulated to determine the set of products that can be assembled together in flexible resources. In practice, modularization step is done manually, as it requires complex engineering knowledge about the processes and the products. First step of the procedure is the overview of the existing resources, as well as the analysis of the 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.

System configuration regards only the set of assembly resources in this case, and relies on the modularization of the assembly system. The modular assembly lines are built up of dedicated, flexible and reconfigurable modules. Most assembly processes are done manually by operators, however, some of the modules can be automated, for extra costs. The assembly modules are configured sequentially according to the successive assembly operations required by the assembled product. The required number of modules as well as the corresponding processing times are known, however, the number of operators can be changed from shift to 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) or a set of products (flexible). 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 [34].

Reconfigurable lines are composed of standard, mobile workstations, configured sequentially according to the successive assembly operations. A standard, mobile reconfigurable module enables to perform a single assembly process 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 in reality 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 necessary fixtures on the modules. The operators prepare the necessary parts that need to be assembled.
- Assembly: The operators assemble the products in the required volume.
- Deconfiguration: After an assembly process is finished, the operators dismantle the lines, and move back the excess workstations, 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.

3.2. Costs of production with different resource types

The general driver of capacity management is to stay competitive in a dynamic environment by keeping the production costs at the lowest possible level while providing the desired production rate. In the paper, a problem is analyzed where total production cost —characterizing the operation of the assembly system during a certain period— is to be minimized. When discussing system configuration and product-resource assignment, usually longer periods are considered as these decisions raises 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 2 depicts the total costs realized in relation to three different system types, within a numerical study. Each point of the chart corresponds to a given configuration, and one can conclude that the correlation between the costs and total capacity requirements is nonlinear, caused by the operational costs that are affected by the dynamic behavior of the system.

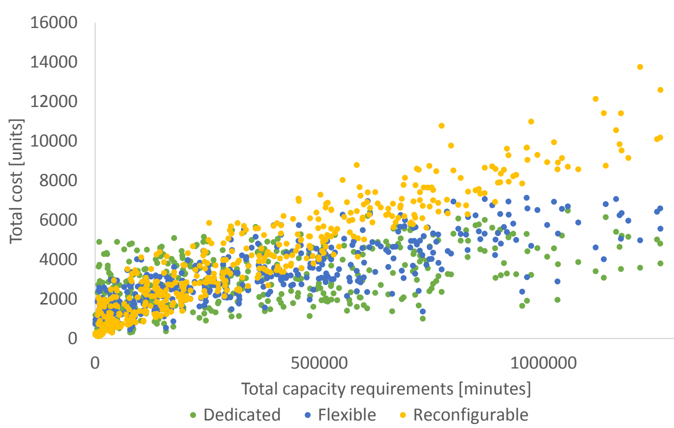

Figure 2: Comparison of the total costs in the three system types (numerical analysis of a case study)

Investment costs mostly depend on the number of products that should be produced, 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 obvious that dedicated resources are more expensive than the other two. 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 increase 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 assigned products. This assumption is justified by Figure 3 with the results of a numerical study, illustrating that linear correlation between the number of assigned products and the investment costs is valid only for the dedicated systems with a static system 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 is in a nonlinear correlation with the number of products.

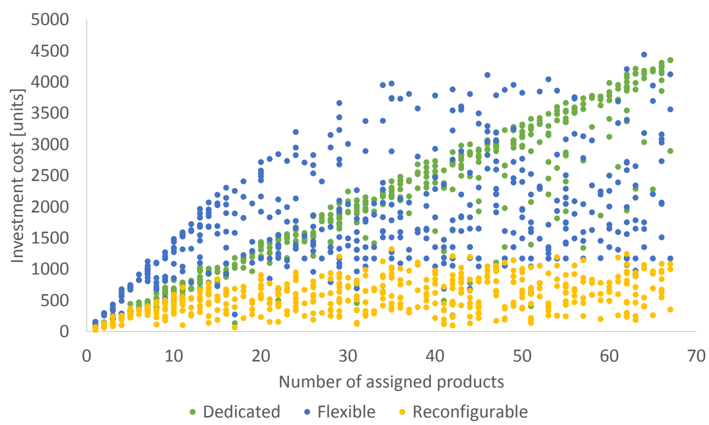

Figure 3: Comparison of the investment costs in the three system types (numerical analysis of a case study)

Besides the investments, operation of the 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 our methodology, the 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 volume costs. This total capacity requirement is the sum of manual operation times t_p^{proc} multiplied by the volume of products. 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 (Fig. 4). The reason for this is the higher throughput of the lines, resulting in shorter makespan than e.g. producing the same volumes in a reconfigurable system, besides, dedicated systems with automated resources require less operators than the flexible and reconfigurable ones.

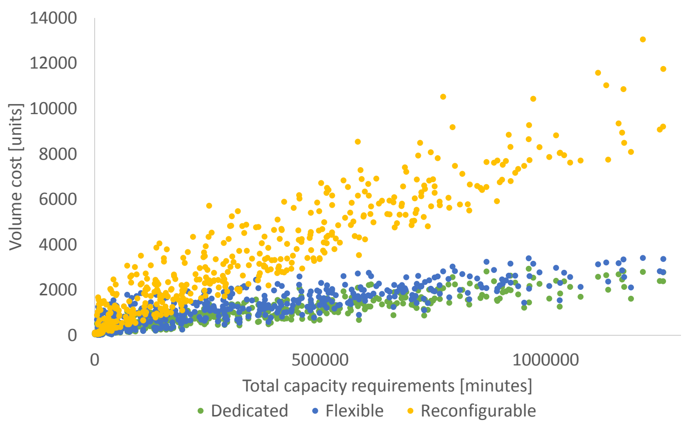

Figure 4: Comparison of the volume-dependent costs in the three system types (numerical analysis of a case study)

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 whole product portfolio needs to be analyzed to configure the assembly system, and 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. In this case, not only investment costs need to be considered, but there is an opportunity to sell the unnecessary resources, e.g. when a product is switched from a dedicated to a reconfigurable system, the excess system components can be sold for a certain price calculated according to the depreciation of the assets. The book value of assets can be calculated by decreasing the value of the previous period 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). Book value can be interpreted as a price, for which a resource can be sold at a certain point of time.

3.3. Production planning 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. In contrast, flexible and reconfigurable systems are characterized with a 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: the performance of modular reconfigurable assembly systems and incurring costs are strongly influenced by the system configuration and also by the applied scheduling policy [35, 36]. Besides the investments, volume-related operational costs in these dynamic systems is also more complex to be estimated, as they can be operated economically if more product types (family) are assigned.

It is also essential that strategic decisions influence the execution of tactical-level production plans, thus the link between these levels is of crucial importance. The configuration of the assembly system with the product-resource assignments and available capacities constrains the decisions when planning the production, therefore, planning aspects need to be considered when configuring system. Production planning in our methodology is responsible for calculating the production lot sizes, with the objective of minimizing the total production costs.

4. Problem statement

Having the boundaries of the analyzed modular system defined, the formal definition of the capacity management problem is provided as it follows. The notations applied in the paper are summarized in Table 1.

4.1. Objective and decisions of capacity management

The objective of capacity management is to match the capacity of the modular assembly system with 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 different assembly resources, and assign the products to these resource sets (Fig. 5). In the paper, three different system types $s \in S$ are considered: reconfigurable ($s = r$), flexible ($s = f$) and dedicated ($s = d$) systems. In the considered problem, the task is to minimize the total cost that incur on 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. Besides, 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 taking right decisions in each time period $u \in U$, assigning the products to one of the three system types. These

Table 1: Nomenclature

Sets	
J	set of modules
N	set of orders
P	set of products
B	subset of products, $B \subset P$
T	set of production planning periods
U	set of strategic planning periods
S	set of system types
K	set of product clusters
Variables	
z^s_{pu}	assign product p to system s in period u
w^s_{pu}	product p is assigned to a different system s in period u
g^s_{bu}	assign a subset b of products to system s in period u
n_j	amount of modules from type j
h_t	headcount of operators in period t
y_{pt}	setup for product p in period t
x_{it}	production of order i in period t (binary indicator)
Parameters	
c^{m}_j	purchase cost of module j
c^{rec}	cost of reconfiguration
c^{set}	cost of a setup
c^{opr}	average cost of an operator per period
c^{opn}	operation cost of a module per time period t
c^{chg}	cost of change (assign a product to another system
c^{dep}	depreciation factor
c_{it}	cost of producing order i in period t
t^{set}_p	setup time of product p
t^{rec}_p	reconfiguration time of product p
t^{proc}_p	the total manual cycle time of product p
t^{shift}	duration of a shift
m^{max}	shop-floor space constraint
m^{space}_s	multiplier of module space requirement in system s
m^{purch}_s	multiplier of module purchase cost in system s
m^{aut}_s	multiplier of automation level in system s
d_i	due date of order i
c^{h}_i	holding cost of order i per period
c^{l}_i	lateness cost of order i per period
q_i	volume of order i
p_i	product of order i
f_{pu}	forecast volume of product p for period u
r_{jp}	required number of module j by product p
r^{avail}_j	number of modules j available in the resource pool
r_{jk}	required number of module j by cluster k
h^{max}	max. total number of available operators
k_p	cluster of product p
Regression functions	
λ^s_u	value of assets in system s and period u
Λ^s_u	investment costs in system s and period u
Γ^s	volume costs of system s
χ	cost of change
Ψ	depreciation costs
β	regression coefficients

actions are 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 necessary modules n_j from each type $j \in J$ also need to be determined (Fig. 5). These investment and system configuration decisions are taken on a strategic level considering volume forecasts f_{pu}, and a longer horizon (typically some years long). Additional complexity in the problem is introduced by the fact that order volumes are changing over time, and forecasts are uncertain.

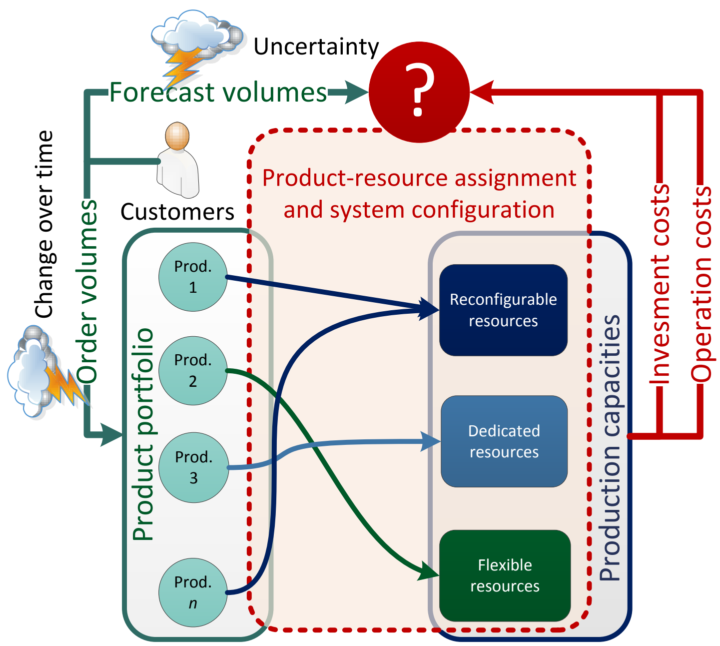

Figure 5: Illustration of the analyzed product-resource assignment and system configuration problem

4.2. Constraints

Although it would be simple to assign each product to dedicated resources to be able to provide the target production rate, this strategy would lead to high production costs due to the facts summarized in Section 3.2. When configuring the system, various constraints need to be considered, e.g. the available shop-floor space $m^{\max}$ and the available human workforce $h^{\max}$. Besides, different cost factors are considered: the purchase cost of the modules m_s^{purch}, the cost of setups c^{set} and reconfigurations c^{rec}, the salaries c^{opr} of the operators and the operation costs c^{opn} of the machines.

In the considered problem, modules of different system types s can have different level of automation m_s^{aut}, affecting 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^{purch} of the modules depend on the system type.

Concluding the above thoughts, the system configuration problem in this paper is solved by combining the advantages 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.

5. Hierarchical capacity management framework

In order to solve the above stated, strategic-level system configuration problem, the tactical level production planning also need to be considered to calculate the investment and operational costs that will certainly incur in the future, respecting the forecast volumes. Relying on multiple decision criteria, diverse cost functions and complex relations among the strategic and tactical decisions, a multi-level, hierarchical capacity management framework is proposed to achieve the objectives stated in Section 4.1. The novelty of the framework stems from the strong link between the configuration and planning levels, applying regression models to approximate the investment and operation costs. The proposed capacity management framework consists of two hierarchical stages: the system configuration and production planning levels. These levels provide input and output for each other, ensuring a tight connection between the decisions, and resulting in feasible plans on both levels (Fig. 6).

5.1. Feedback link between the decision levels: Function approximation

As system configuration and available capacities represent strict constraints when planning the production, strategic decisions need to consider tactical level aspects as well. Assigning a product to a system type implies

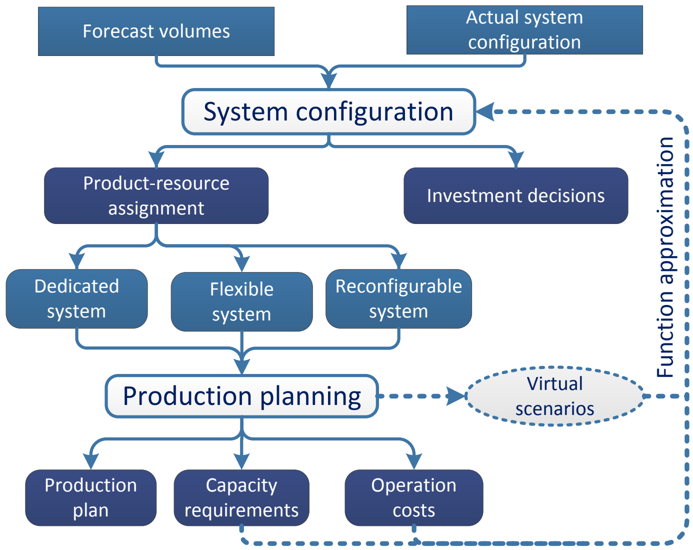

Figure 6: Capacity management framework for modular assembly systems.

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 the tactical to the strategic level to approximate the costs that are relevant on the strategic level.

This can be achieved by solving the production planning model on several virtual scenarios, representing possible real situations. In case the correlation among the input variables (order stream) and the corresponding 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. Great advantage of the regression models is their integrability in optimization models: in case simple approximation functions (e.g. linear models) 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 for each product are known a-priori, but the necessary investment cannot be calculated without information about the costs that will characterize the system's operation. As resource sharing in flexible and reconfigurable assembly systems strongly influences the system's performance and thus the operational costs, neglecting the capacity constraints in the production planning model of the virtual scenarios and introducing the capacities as decision variables results in 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 can be applied in the mathematical model of the system configuration as constraints: having linear approximation functions, the linearity of the existing optimization model can be kept. As system configuration and production planning models apply different planning horizon and time periods, the results of virtual scenarios are scaled to provide reliable input for the system configuration.

5.2. Production planning

5.2.1. Constraints and decisions in production planning

Regression models are defined over the solutions of the production planning model, therefore, this part of the capacity management framework is described first. As previously stated, production planning in this methodology is responsible for determining the production lot sizes applying a discrete time horizon T, with the resolution of one working shift $t \in T$. Orders $i \in N$ are given for the planning period, and an order is characterized by its completion due date d_i, inventory holding cost c_i^{h}, the cost of lateness c_i^{l}, and the volume of ordered products q_i. As there are individual due dates for each order, both early delivery and lateness are penalized with a deviation cost c_{it} as follows:

$$c_{it} = \begin{cases} c_i^{\mathrm{h}}(d_i - t) & \text{if } t < d_i \\ c_i^{\mathrm{l}}(t - d_i) & \text{otherwise} \end{cases} \tag{1}$$

The objective of the production planning model is to minimize the total costs that incur over the planning horizon, defined as the sum of deviation, setup, reconfiguration, operator and machine operation costs (2). Decision variables are the execution time (shift) of the orders (x_{it}), specifying if order i is assembled in shift t or not. Calculation of the setups is possible by introducing the continuous indicator variable (y_{pt}) that gives if product p is produced in shift t. In this model, a virtual operator pool is defined, therefore, the number of operators is a decision variable that is set as a real type in order

to boost the computation. Accordingly, the defined production planning model for the characterized modular assembly system is the following:
minimize

$$\sum_{t\in T} h_t c^{\text{opr}} + \sum_{p\in P}\sum_{t\in T} y_{pt} c^{\text{set}} + \sum_{t\in T}\sum_{i\in N} x_{it} c_{it} + \sum_{t\in T}\sum_{i\in N}\sum_{j\in J} c^{\text{opn}} x_{it} r_{jp_i} \tag{2}$$

subject to

$$\sum_{t\in T} x_{it} = 1 \quad \forall i \in N \tag{3}$$

$$h_t \le \sum_{j\in J} n_j \quad \forall t \in T \tag{4}$$

$$x_{it} \le y_{pt} \quad \forall t \in T, p = p_i, i \in N \tag{5}$$

$$\sum_{i\in N} x_{it} q_i t_p^{\text{proc}} m_s^{\text{aut}} + y_{pt} t_p^{\text{set}} \le h_t t^{\text{shift}} \quad \forall t \in T, p = p_i \tag{6}$$

$$h_t \in \mathbb{Z}^+ \quad n_j \in \mathbb{Z}^+ \quad y_{pt} \in \mathbb{Z}^+ \quad x_{it} \in \{0,1\} \tag{7}$$

The first constraint states that each order can be assigned to only one time period t, therefore, order splitting is not allowed (3). As modules are operated by a single operator, the headcount of operators in each shift is limited by the total number of the simultaneously applied modules (4). Constraint (5) defines the number of setups in each shift, while constraint (6) specifies the requested number of operators. In this case, both setup time as well as automation degree of the different systems are considered. In case of the reconfigurable system, this constraint is modified with the additional time of the reconfigurations that is $y_{pt} t_p^{\text{rec}} \quad \forall p \in P | p = p_i$.

5.2.2. Planning model of virtual and real scenarios

Further, 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 is used to calculate real plans for definite order sets, besides, virtual scenarios and the corresponding plans are also calculated to define the regression models upon. These two operation modes are distinguished when specifying the following, system dependent constraints: while in real planning situations the number of available resources is given, the purpose of the regression models is to estimate this value. Therefore, the number of modules n_j from each type

$j \in J$ is applied as constraint in the real planning case, whereas in the virtual case, it is part of the objective function.

In case of the dedicated system, the calculation of necessary modules is straightforward: it equals the total number of modules from each type required by the products that are assigned to dedicated resources (9). Dynamics of the reconfigurable system is different, only the assembly processes constrain the necessary number of modules (8). Operation of the flexible system is slightly similar to the reconfigurable case, however, assembly resources are shared among a limited set of products (clusters) only. Equation (10a) specifies the number of modules for each cluster. In this model, it equals to the maximal number of modules for each types, considering all products in the cluster. This representation guarantees that all products can be assembled with the least possible modules. The number of applied modules must be higher than this value (10b).

Reconfigurable:

$$\sum_{p \in P} r_{jp} y_{pt} \leq n_j \quad \forall j \in J, t \in T \tag{8}$$

Dedicated:

$$\sum_{p \in P} r_{jp} = n_j \quad \forall j \in J \tag{9}$$

Flexible:

$$r_{jk} = \max_{p \in P} \{ r_{jp} | k_p = k \} \quad \forall j \in J, k \in K \tag{10a}$$

$$\sum_{k \in K} \sum_{p \in P} r_{jk} y_{pt} \leq n_j \quad \forall j \in J, t \in T \tag{10b}$$

Having the values n_j defined for each system type, the production planning models for the real and virtual scenarios can be separated. In the real planning cases with given number of resources, constraints (8)-(10b) 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 (8)-(10b) 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 (applied instead of (2)) of the virtual scenarios is the following:

$$\begin{aligned} \text{minimize} \sum_{t\in T} h_t c^{\text{opr}} + \sum_{p\in P}\sum_{t\in T} y_{pt} c^{\text{set}} + \sum_{t\in T}\sum_{i\in N} x_{it} c_{it} + \\ + \sum_{t\in T}\sum_{i\in N}\sum_{j\in J} c^{\text{opn}} x_{it} r_{jp_i} + \sum_{j\in J} n_j c_j^{\text{m}} m_s^{\text{purch}} \end{aligned} \tag{11}$$

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

5.3. Multi-period system configuration model

5.3.1. Decision variables and constraints of the system configuration model

Decision variables z_{pu}^s specify the system, to which products are assigned over time. Important to identify that the length, and thus the notation of the 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 4— is the following:

minimize

$$\Psi + \chi + \sum_{s\in S} \Gamma^s + \sum_{s\in S}\sum_{u\in U} \Lambda_u^s \tag{12}$$

subject to

$$\sum_{s\in S} z_{pu}^s = 1 \qquad \forall p \in P, u \in U \tag{13}$$

$$\sum_{j\in J}\sum_{p\in P}\sum_{s\in S} z_{pu}^s r_{jp} m_s^{\text{space}} \quad \leq m^{\max} \qquad \forall u \in U \tag{14}$$

$$\sum_{s\in S}\left(\beta_{s0}^{\text{op}} + \beta_{s1}^{\text{op}} \sum_{p\in P} z_{pu}^s f_{pu} t_p^{\text{proc}}\right) \leq h^{\max} \quad \forall u \in U \tag{15}$$

$$w_{pu}^s \geq z_{pu}^s - z_{p,u-1}^s \qquad \forall p \in P \tag{16}$$

$$\Lambda_u^d \geq \sum_{j\in J}\sum_{p\in P} w_{pu}^s n_j c_j^{\text{m}} m_d^{\text{purch}} \quad s = d, u \in U \tag{17}$$

$$\Lambda_u^s \geq \lambda_u^s - \lambda_{u-1}^s \quad s \in \{r, f\}, u \in U \tag{18a}$$

$$\Lambda_u^s \geq 0 \qquad \forall s \in S, u \in U \tag{18b}$$

$$\chi = c^{\text{chg}} \sum_{p \in P} \sum_{u \in U} \sum_{s \in S} \sum_{j \in J} w_{pu}^{s} n_j \tag{19}$$

$$\Psi = c^{\text{dep}} \sum_{s \in S} \sum_{u \in U} \sum_{p \in P} \sum_{j \in J} z_{pu}^{s} r_{jp} m_s^{\text{purch}} c_j^{\text{m}} \tag{20}$$

$$g_{bu}^{s} \geq z_{pu}^{s} \quad b \in B = \{1 \ldots p_b\} \tag{21}$$

$$z_{pu}^{s} \in \{0,1\} \quad w_{pu}^{s} \in \{0,1\} \quad g_{bu}^{s} \in \{0,1\} \tag{22}$$

The objective function (12) is the total cost resulted by the assignment of the products to the different resource types. The function has four main elements: the cost Ψ of using resources (analogous to the depreciation of the resources, if linear formula is applied), the cost χ 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 (13) states that a product can be assigned to only one of the three system types in a certain period u. The next inequalities represent the limited shop-floor space (14) and the maximal number of operators per period (15). 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 as input variables.

5.3.2. Elements of the objective function

Having the operation characterized by the previous constraints, further parts of the model specify the elements of the objective function. 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 $\Gamma^s \left(z_{pu}^s, g_{bu}^s\right)$, as detailed in (23). 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 products are summed and multiplied with the purchase cost of the modules (17). In case of reconfigurable and flexible resources, the investment costs are calculated in two steps: first, the value of assets (λ_u^s) realized at a certain period u is approximated with regression models in a form of $\lambda_u^s(z_{pu}^s)$ for resource types $s \in \{r, f\}$ as detailed in (24). 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 value of shared resources in the flexible and reconfigurable systems are additive by nature, the investment costs (Λ_u^s) that are realized as a result of a decision taken in u equals to the difference in the values of assets (18a) in two consecutive periods $\left(\lambda_u^s - \lambda_{u-1}^s\right)$. The cost of change χ incurs when the assignment of a product is switched as a result of a strategic decision, and additional efforts in design and installation is required. Besides the investment costs, costs of change in the model prevent the time-to-time reassignments of products from one system type to another (19). As stated earlier, excess modules can be sold, however, their value 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, depends only on the assignments (z_{sp}^u), and can be calculated by the formula (20).

Decision variables g_{bu}^s express the option to assign selected subsets $B \subset P, b \in B$ of products to the same system type, in order to utilize its advantages. This is mainly valid for reconfigurable and flexible systems, which are designed to produce more 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.

6. Case study: Capacity management in the automotive sector

The proposed methodology is evaluated with the results of a real industrial case study from the automotive sector. In its assembly segment, the company has to manage the production of 67 main product types that are characterized with very diverse yearly volumes, and some uncertainty in the forecasts. The available human workforce as well as the shop-floor space is limited, thus finding an optimal capacity management policy results in significant benefits for the company.

In this case, modularization is based on a set of standard assembly processes (e.g. manual screwing, pressing, greasing etc.), assigned to assembly modules. In this way, it is assumed that each product can be assembled in a modular assembly system with the desired quality, independently from the type of the resource. As the assembly processes are simple and the products are small-sized, lightweight *plug and produce* modules can be applied in the assembly system.

6.1. Approximation of the costs with regression models

In order to analyze the costs that characterize the operation of flexible and reconfigurable systems, the tactical production planning model was solved first by applying a set of virtual scenarios. These scenarios were generated and solved in *FICO Xpress*® software, applying its built-in optimization solver[1]. In each virtual scenario, the data was generated randomly by the following rules. The length of the planning horizon was 40 production shifts, the number of orders were 1–350, and the order volumes were 1–800 per order. The production planning problem (Section 5.2.1) was solved 450 times for each resource type $s \in S$. Then, the three resulted datasets were split up into training and test sets, applying random sampling and 1:2 ratio. The regression models were all defined over the training datasets including 150 observations, and evaluated by the test sets consisting of 300 observations. In our methodology, eight regression models were defined in total: two for the λ_u^s, three for the Γ^s functions and three models to determine the operator requirements (15). In each model building, forward stepwise method was applied to select the predictor variables. Moreover, nonnegative linear regression with the *Lawson-Hanson algorithm* was applied in order to avoid unrealistic function approximation with possible negative coefficients [37]. The main fit properties of the regression models are summarized in Table 2.

Table 2: Fit properties of the regression models

	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

[1]All the computational experiments presented in the paper 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.

As for the predictor variables of the models, the total volumes (forecast) were applied to determine the volume costs. These models tackle the non-linear interaction terms among the products, applying the product subset variables (g_{bu}^{s}) as stated in section 5.3.2. In our case, nine subsets were applied; the products of subsets are selected during the model fitting procedure:

$$\Gamma^{s} = \beta_{s0}^{\text{vol}} + \sum_{u\in U}\sum_{p\in P}\left(\beta_{sp}^{\text{vol}} z_{pu}^{s} f_{pu}\right) + \sum_{u\in U}\sum_{\substack{b\in B\\ b=p}}\left(\beta_{sb}^{\text{vol}} g_{bu}^{s} f_{pu}\right) \quad \forall s \in S \tag{23}$$

In case of the flexible and reconfigurable resources, prediction of λ_{u}^{s} for the values of assets was done with the number of assigned products and the total capacity requirements:

$$\lambda_{u}^{f} = \beta_{s0}^{\text{fix}} + \sum_{p\in P}\left(\beta_{s1}^{\text{fix}} z_{pu}^{s} + \beta_{sp}^{\text{fix}} z_{pu}^{s} f_{pu} t_{p}^{\text{proc}}\right) \qquad s \in \{r, f\} \tag{24}$$

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 (15).

6.2. System configuration study

6.2.1. Introduction of the compared methods

In industrial practice, firms usually solve the system configuration problem (supposing that different resource types are available, see Section 4.1) based on individual product types, neglecting the portfolio-wide factors, more specifically, the underlying correlations among the assignment of product to different resource types. In these commonly applied product-based approaches, system designers combine 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. 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 are typically assembled in modular, reconfigurable systems. The latter products are mostly the prototypes, or the ones in their end-of-lifecycle or spare parts for aftermarket.

As there is no available, specific optimization based methodology to solve the analyzed problem (Section 2.2), the proposed capacity management workflow was compared to the above described, rule-based practical methodology

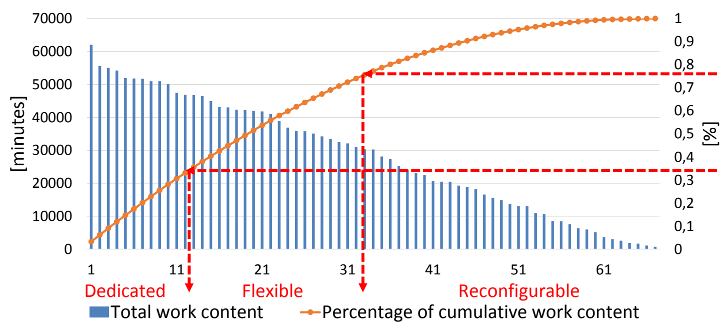

Figure 7: Representation of the CR rule on the Pareto-chart of the products' work contents

within a comparative study. Four different methods were analyzed by solving the system configuration problem over multiple periods. The product-based solutions applied in the industrial practice was 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 methodology. 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 percentage capacity requirements were considered, but the products were sorted in a descending order according to their total capacity requirements, and the cumulative percentages were applied to assign them to different resource types. This method is depicted by an exemplar Pareto-chart of the work contents on Figure 7. In the second rule based method called IR, the 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 methodology proposed in the paper was also implemented in two different ways within the study: the first version —called LO— considered a fixed horizon, and determined the best system configuration strategy by looking ahead 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 were 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 8.

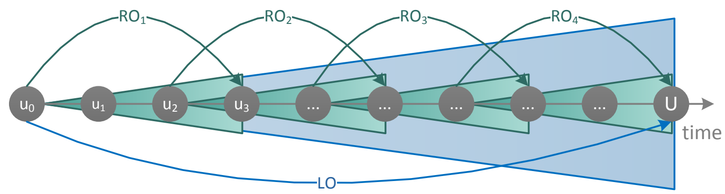

Figure 8: Representation of the replanning periods (arrows) and time horizons of the rolling horizon RO, (green) and lookahead LO (blue) methods with the confidence regions of the volume forecasts (triangles)

6.2.2. Scenarios of the study

In the analyzed problem, $|U| = 10$ periods were considered, on which volume forecasts were available, however, uncertainty had to be considered as realized order volumes in period u might differ by 10% from the volumes predicted in $u - 1$ (confidence regions are represented by Figure 8). Therefore, weighted averages of the forecast volumes f_{pu} were considered in the system configuration problem, with five periods lookahead. In each period u, decision variables z_{sp}^u were determined based on the forecasts, and the necessary investments were calculated. Then, the production planning model was run to calculate the costs that will incur in period u. In this case, the cumulated forecast volumes were split into real customer orders, simulating maximum 10% deviation (normal distribution) in the total volumes by generating individual orders $i \in N$ with random generated (with a realistic, uniform distribution over the horizon) due dates d_i and order volumes q_i. 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 6.1).

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 the 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 scenario is valid for the majority of the 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 case 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 the product portfolio that can be either balanced or diverse. In case of the *diverse (DIV)* portfolio, significant differences could be among the total capacity requirements of products in a given time period: there were 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 were similar (the volumes of processing times can be diverse, but the overall capacity requirement were in the same order of magnitude).

This resulted in four main scenarios (the combinations of the above factors), that were all analyzed within the study. In each scenarios, 15 different test cases were generated with similar main characteristics, however, with different customer orders as well as changed 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.

6.2.3. Discussion of the results

The main numerical results of the study are summarized in two boxplot charts. In both charts, the results are given in percentage values, to be comparable. 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 boxplot visualize the average, maximum and minimum values, as well as the percentiles of the 15 test cases per scenarios and methods.

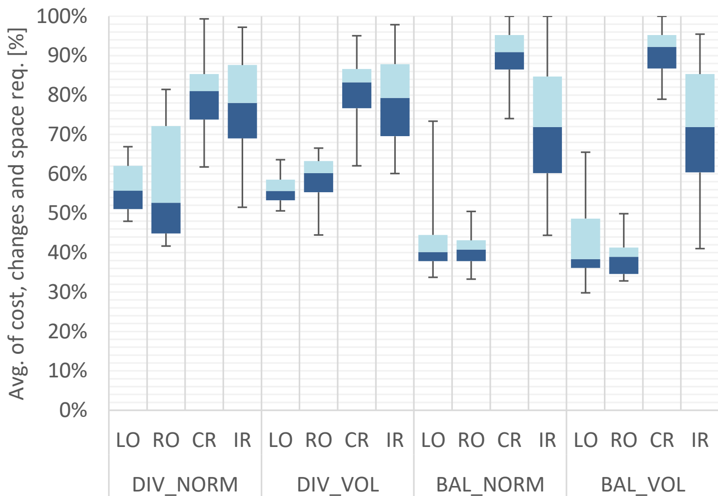

Figure 9: Results of the case study: average values of the resulted costs (12), changes (19) and space requirements (14)

The first boxplot (Fig. 9) visualizes the results of average of 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 them. These factors are also summarized in the first comparison which depicts 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 methodology 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 had 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, the deviation of the results was also rather high.

In contrast to the previous boxplot, Fig. 10 summarizes only the overall costs obtained by the different system configuration methods. The most

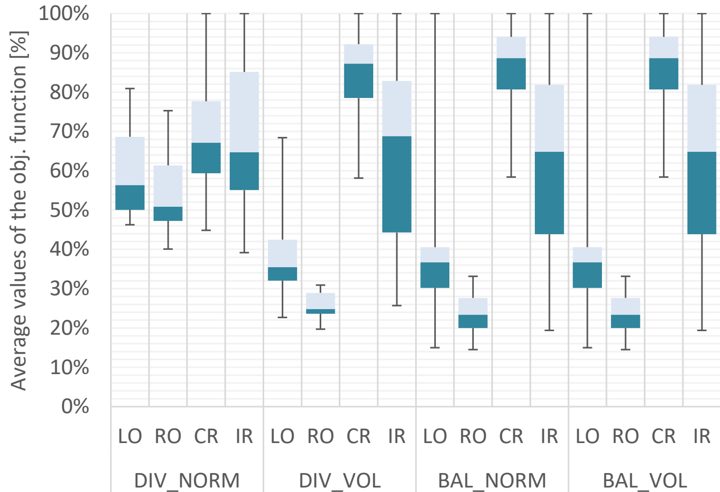

Figure 10: Results of the case study: overall costs (12)

obvious difference here is the high deviation of the costs resulted by the LO method, which is 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, the average of the solutions were still better than the ones 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.

Summarizing the results of the case study, one can conclude that the performance of rule based approaches is decreasing as uncertainty is increasing (hectic lifecycle), or the portfolio is composed of products with similar total capacity requirements. In those cases, general practical approaches becomes unstable, as the calculated system configuration cannot cope with the uncertainty of the forecasts, nor with the frequent reassignment of the product to the different system types. Besides, it is also unclear which rule needs to be applied in a given case, as their performance highly depends on 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, as it considers portfolio-wide correlations among the processes, and optimizes the assignment 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.

7. Conclusions

The co-existence of reconfigurable, flexible and dedicated resources is a relevant industrial topic, however, only a few approaches are available for the long term and medium term capacity planning for these systems. In the paper, a novel capacity management methodology was proposed for modular assembly systems that aims at minimizing the operating and investment costs along the lifecycle of the products. 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. Besides, system configurations are determined based on the entire portfolio considering the correlations among the processes, in contrast to the previously existing, individual product based methods. The proposed method results in significant cost savings in the long run, compared to the most commonly applied rule based approaches.

Besides the above features, the greatest 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 methodology 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.

As for the outlook and related future work, robust optimization reformulation of the models aimed to be implemented, to consider the possible uncertainty of the parameters when solving the optimization model by applying uncertainty sets. In this way, the uncertain changes in costs (e.g. labor costs and/or machine purchase costs) can be represented in the constraints, so as to optimize the system configuration accordingly.

Acknowledgments

This research has been supported by the GINOP-2.3.2-15-2016-00002 grant on an "Industry 4.0 research and innovation center of excellence"; and by the Hungarian Scientific Research Fund (OTKA) under Grant No. 113038.

References

[1] T. Tolio, D. Ceglarek, H. ElMaraghy, A. Fischer, S. Hu, L. Laperrière, S. T. Newman, J. Váncza, Species–co-evolution of products, processes and production systems, CIRP Annals-Manufacturing Technology 59 (2) (2010) 672–693.

[2] H. A. ElMaraghy, G. Schuh, W. ElMaraghy, F. Piller, P. Schönsleben, M. Tseng, A. Bernard, Product variety management, CIRP Annals-Manufacturing Technology 62 (2) (2013) 629–652.

[3] A. Bryan, J. Ko, S. Hu, Y. Koren, Co-evolution of product families and assembly systems, CIRP Annals-Manufacturing Technology 56 (1) (2007) 41–44.

[4] B. Lotter, H.-P. Wiendahl, Changeable and reconfigurable assembly systems, in: Changeable and Reconfigurable Manufacturing Systems, Springer, 2009, pp. 127–142.

[5] E. Westkämper, Assembly and disassembly processes in product life cycle perspectives, CIRP Annals-Manufacturing Technology 52 (2) (2003) 579–588.

[6] S. J. Hu, J. Ko, L. Weyand, H. ElMaraghy, T. Lien, Y. Koren, H. Bley, G. Chryssolouris, N. Nasr, M. Shpitalni, Assembly system design and operations for product variety, CIRP Annals-Manufacturing Technology 60 (2) (2011) 715–733.

[7] H. A. ElMaraghy, T. AlGeddawy, A. Azab, W. ElMaraghy, Change in manufacturing–research and industrial challenges, in: Enabling Manufacturing Competitiveness and Economic Sustainability, Springer, 2012, pp. 2–9.

[8] D. W. He, A. Kusiak, Design of assembly systems for modular products, Robotics and Automation, IEEE Transactions on 13 (5) (1997) 646–655.

[9] G. Lanza, K. Peter, J. Rühl, S. Peters, Assessment of flexible quantities and product variants in production, CIRP Journal of Manufacturing Science and Technology 3 (4) (2010) 279–284.

[10] H. ElMaraghy, W. ElMaraghy, Smart adaptable assembly systems, Procedia CIRP 44 (2016) 4–13.

[11] R. Fernandes, J. B. Gouveia, C. Pinho, Product mix strategy and manufacturing flexibility, Journal of Manufacturing Systems 31 (3) (2012) 301–311.

[12] H.-P. Wiendahl, H. A. ElMaraghy, P. Nyhuis, M. F. Zäh, H.-H. Wiendahl, N. Duffie, M. Brieke, Changeable manufacturing-classification, design and operation, CIRP Annals-Manufacturing Technology 56 (2) (2007) 783–809.

[13] H. A. ElMaraghy, Flexible and reconfigurable manufacturing systems paradigms, International journal of flexible manufacturing systems 17 (4) (2005) 261–276.

[14] M. Bruccoleri, G. Perrone, Economical models for reconfigurable manufacturing systems, in: Reconfigurable manufacturing systems and transformable factories, Springer, 2006, pp. 629–641.

[15] M. Onori, N. Lohse, J. Barata, C. Hanisch, The ideas project: plug & produce at shop-floor level, Assembly automation 32 (2) (2012) 124–134.

[16] Y. Koren, M. Shpitalni, Design of reconfigurable manufacturing systems, Journal of Manufacturing systems 29 (4) (2010) 130–141.

[17] G. Zhang, R. Liu, L. Gong, Q. Huang, An analytical comparison on cost and performance among DMS, AMS, FMS and RMS, in: Reconfigurable manufacturing systems and transformable factories, Springer, 2006, pp. 659–673.

[18] H. ElMaraghy, M. Manns, Transition of interarrival time patterns between automated and manual configurations of assembly systems, Journal of Manufacturing Systems 26 (1) (2007) 1–11.

[19] X. Meng, Modeling of reconfigurable manufacturing systems based on colored timed object-oriented petri nets, Journal of Manufacturing Systems 29 (2) (2010) 81–90.

[20] Y. Koren, General RMS characteristics. Comparison with dedicated and flexible systems, in: Reconfigurable manufacturing systems and transformable factories, Springer, 2006, pp. 27–45.

[21] C. Renzi, F. Leali, M. Cavazzuti, A. Andrisano, A review on artificial intelligence applications to the optimal design of dedicated and reconfigurable manufacturing systems, The International Journal of Advanced Manufacturing Technology 72 (1-4) (2014) 403–418.

[22] O. Kuzgunkaya, H. ElMaraghy, Economic and strategic perspectives on investing in rms and fms, International Journal of Flexible Manufacturing Systems 19 (3) (2007) 217–246.

[23] A. M. Deif, W. ElMaraghy, Investigating optimal capacity scalability scheduling in a reconfigurable manufacturing system, The International Journal of Advanced Manufacturing Technology 32 (5-6) (2007) 557–562.

[24] P. Renna, A decision investment model to design manufacturing systems based on a genetic algorithm and monte-carlo simulation, International Journal of Computer Integrated Manufacturing (2016) 1–16.

[25] A. M. Youssef, H. A. ElMaraghy, Optimal configuration selection for reconfigurable manufacturing systems, International Journal of Flexible Manufacturing Systems 19 (2) (2007) 67–106.

[26] P. Renna, Capacity reconfiguration management in reconfigurable manufacturing systems, The International Journal of Advanced Manufacturing Technology 46 (1-4) (2010) 395–404.

[27] G. Putnik, A. Sluga, H. ElMaraghy, R. Teti, Y. Koren, T. Tolio, B. Hon, Scalability in manufacturing systems design and operation: State-of-the-art and future developments roadmap, CIRP Annals-Manufacturing Technology 62 (2) (2013) 751–774.

[28] S. S. Elmasry, A. M. Youssef, M. A. Shalaby, Investigating best capacity scaling policies for different reconfigurable manufacturing system scenarios, Procedia CIRP 17 (2014) 410–415.

[29] A. M. Deif, W. H. ElMaraghy, A control approach to explore the dynamics of capacity scalability in reconfigurable manufacturing systems, Journal of Manufacturing Systems 25 (1) (2006) 12–24.

[30] G. Lanza, S. Peters, Integrated capacity planning over highly volatile horizons, CIRP Annals-Manufacturing Technology 61 (1) (2012) 395–398.

[31] W. Wang, Y. Koren, Scalability planning for reconfigurable manufacturing systems, Journal of Manufacturing Systems 31 (2) (2012) 83–91.

[32] M. Abbasi, M. Houshmand, Production planning and performance optimization of reconfigurable manufacturing systems using genetic algorithm, The International Journal of Advanced Manufacturing Technology 54 (1-4) (2011) 373–392.

[33] O. Ceryan, Y. Koren, Manufacturing capacity planning strategies, CIRP Annals-Manufacturing Technology 58 (1) (2009) 403–406.

[34] D. Gyulai, B. Kádár, A. Kovács, L. Monostori, Capacity management for assembly systems with dedicated and reconfigurable resources, CIRP Annals-Manufacturing Technology 63 (1) (2014) 457–460.

[35] D. Gyulai, B. Kádár, L. Monostori, Capacity planning and resource allocation in assembly systems consisting of dedicated and reconfigurable lines, Procedia CIRP 25 (2014) 185–191.

[36] D. Gyulai, Z. Vén, A. Pfeiffer, J. Váncza, L. Monostori, Matching demand and system structure in reconfigurable assembly systems, Procedia CIRP 3 (2012) 579–584.

[37] K. M. Mullen, I. H. M. van Stokkum, nnls: The Lawson-Hanson algorithm for non-negative least squares (NNLS), r package version 1.4 (2012).
URL `http://CRAN.R-project.org/package=nnls`