

Robust production planning and capacity control for flexible assembly lines

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Abstract: The frequently changing order stream and high product variety require robust planning and control approaches, as well as a flexible system structure in order to fulfill the highest possible customer service level and to keep the production costs on a reasonable level. In the paper, a combined production planning and capacity control method for assembly lines is proposed aiming at balancing the workload of the human operators and decreasing the overall production costs on a given time horizon.

Instead of using the idealistic cycle times and simple manufacturing control rules, the proposed planning and control methodology is based on adaptive calculations taken from continuously updated historical production data. The manufacturing execution-level data is applied for building regression models predicting the capacity requirements of the future production scenarios. Besides, the historical data is also used as direct input of discrete-event simulations, to determine the proper control policies of human operator allocations for the different scenarios mentioned above. In order to calculate reliable and feasible production plans, the regression models and control policies are integrated in a mathematical programming model that minimizes a cost function representing the total production costs.

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1. INTRODUCTION

High product variety, competitive market and the fluctuating order stream are important characteristics of today's manufacturing industry. Taking the automotive sector into consideration, suppliers have to meet strict due dates and provide high quality products for their customers, while keeping their production costs on the lowest possible level. Flexible manufacturing/assembly systems exist for decades, however, they are still one of the most fundamental solutions to react to the changes and disturbances efficiently.

1.1 Flexible assembly lines

In the automotive industry, the cars themselves are usually assembled on platform-based mixed-model assembly lines, while most of the main components are produced in flexible assembly lines. The general difference between these solutions lie in the control flexibility of the lines: while the mixed model lines are capable of assembling an arbitrary changing sequence of product variants without any changeovers, flexible flow lines are designed for producing different product variants in batches. Therefore, in latter systems precise production planning is crucial to minimize the changeovers required to setup the line from one product variant to another. Besides, most of these lines are not fully automated, which means human operators are required to perform certain assembly tasks.

Focusing on the manually operated flexible assembly lines—which is the main topic of the paper—the most general planning decisions include the identification of required capacities and production lot sizes. In the paper we focus on the mid-term planning of the assembly lines that provides cost-optimal plans with the calculated production lot-sizes, release dates as well as the capacity requirements. In order to handle the changes and disturbances in a robust way, the proposed planning method is combined with a lower level capacity control, which means the assignment of operators to the different tasks along the production plan. In our view capacity control generally decides about the work hours and when and to which workstations human resources are allocated (Rossi and Lödding, 2012). While the objective of the mid-term planning is to decrease costs by eliminating the unnecessary changeovers and decreasing the stock levels, the capacity control is responsible for balancing the workload of the operators and eliminating the idle times.

The paper introduces a method, which combines mid-term planning and capacity control by applying mathematical programming and discrete-event simulation. First, the capacity control policies for each product variants are determined to minimize the negative effects of shop-floor level disturbances like reject rates and machine breakdowns. Then the control policies are integrated in the mid-term planning computation via regression models calculating the real capacity requirements.

1.2 Robustness in production planning and control

In general, production planning methods rely on deterministic input data hence fail to cope with a dynamic effects of the execution environment and the considerable uncertainty of the underlying planning information. In order to face the challenges, robust techniques are required which can provide feasible production plans. Robustness in production planning involves refined approaches that aim at handling predictable or unpredictable changes and disturbances. They respond to the occurrence of uncertain events (reactive approaches) or protect the performance of the plan by anticipating to a certain degree the occurrence of uncertain events (proactive approaches) (Tolio et al., 2011).

In our methodology robust planning is the logical layer of the robust production. A production plan is called robust if it results in an acceptable level of the selected performance indicators even if unpredictable disruptions occur during the execution of the plan. The robustness of the systems often works against other efficiency criteria, hence, it means a trade-off is required if the objective is to increase system's robustness. Efficient ways of taking uncertainties into account, and to achieve more robust solutions are either applying stochastic models (Csáji and Monostori, 2008) (e.g., by estimating the underlying stochastic processes), or using adaptive and cooperative approaches which allows prompt responses to changes and disturbances (Monostori et al., 2010).

1.3 Production planning for flexible assembly lines

Generally, the production and supply-chain planning tasks are represented with a three-stage hierarchy (strategic, tactical and operational levels), where the middle, tactical level is responsible for the aggregate production planning. These planning problems are usually represented by mixed-integer programming (MIP) models that can be solved by systematic algorithms (e.g. branch and bound) or heuristics, even though the \mathcal{NP} -complete nature of the problems. These planning problems usually apply a discretized time horizon, and calculate the optimal plan by assigning the production batch releases to the identical time slots (time buckets). Besides the time representation, an important reason for using integer variables in such planning models is the existence of important discrete parameters like setup times, setup costs and machine assignment decisions (Pochet and Wolsey, 2006). Although efficient methods exist to solve those problems in an optimal or quasi-optimal way, large-scale problem instances occurring in industrial practice are still often hard to solve in a reasonable time, which is always an important requirement in practice.

The planing models applied for the manually operated flexible assembly lines typically include the constraints of due-dates, human and machine capacities and setups. The objective functions of these models are usually the minimization of the production costs including the cost of the operation, setups, inventories and backlogs (if allowed) (Sillekens et al., 2011). Even though precise modeling and efficient solver methods are available, these models provide plans which usually quickly become unfeasible

in the execution phase due to the variability of some important parameters (i.e. manual processing times are usually a stochastic). Similarly, machine breakdowns and reject/scrap rates causing rework are disregarded in most of the planning models.

1.4 Simulation-based optimization with regression models

In order to consider these important factors already in the mid-term plans, the paper introduces a novel simulation-based optimization technique production planning of flexible lines. Advanced simulation-based optimization methods exist for decades now, and they are already applied to solve production planning problems. In general, they consist of a mathematical optimization model in which the objective function or constraint(s) are represented by functions that are approximated by using the results of simulations (Azadivar, 1999). The reason for applying simulation in these cases are usually the computational complexity or the lack of analytical expression of the objective function and/or constraints. These challenges are often faced when stochastic functions have to be represented in the optimization models (e.g. lead time as a stochastic function of the in-process buffer levels).

In production planning, simulation-based optimization is usually applied in an iterative form, when some of the parameters are modified after executing the calculated plan in a simulation environment. The parameters can be iteratively adjusted according to the results of the simulation, until the target values of the performance indicators are reached (Byrne and Hossain, 2005; Laroque et al., 2012). In contrast, a simulation-based optimization method is proposed in the paper that relies on linear regression models instead of iterations, thus requires less computation and always relies on up-to-date data. Although linear regression models may seem overly simplistic, they represent properly practical problems and can outperform more sophisticated models which require higher computational effort.

2. PROBLEM FORMULATION

2.1 Production and capacity planning

In the paper a production planning problem is considered, where the planner has to decide about both, the production lot-sizes of different product variants and the release dates of the lots. The target production system is a manually operated, flexible flow assembly line built-up by sequentially coupled workstations. The line is operated in an unpaced way, which means that there is no conveyor belt for the material flow but the operators pass the products from one station to another. The number of operators is less than the number of workstations, therefore, different capacity control policies can be applied to operate the line, depending on the number of operators and the operator-task assignments. The assembly line includes at least one testing station that performs a quality check on every product. The products that do not pass the test proceed to a manual rework station that is separated from the line. After performing the rework, the repaired products are retested again. A lot should totally be completed before a new one is started on the line.

The production orders of the different variants are available for a certain planning horizon that is split up into a set production shifts. Each order can be characterized by its volume and a specific due date. Make-to-stock option is available in every shift, therefore in case of capacity shortage, orders can be fulfilled from stocks, however, holding inventory is associated with extra costs. Order fulfillment after the due date is possible (backlogging) but also penalized with extra costs. The objective of the mid-term planning is to provide an optimal, executable plan that is based on the minimization of the production costs on a certain horizon, and to increase the utilization of the capacities (machines and human operators).

2.2 Capacity control

Within the capacity control part of our methodology, the proper assignment of the operators to the assembly tasks is solved, in order to balance their workload and decrease the idle times caused by the shifting bottleneck —based on the assembled product variant— and the reject rates. In this case, the objective is to determine the best assignment policies for each product variant and each possible number of operators. It means that the number of operators can be changed from shift to shift, according to the production rates. However, more production lots are released in one shift requiring different operator-task assignments while the number of the operators cannot be changed.

Usually, standard work instructions and corporate policies define how to operate the lines with a given number of operators, however, they are all based on norm times and idealistic data. In order to define proper capacity control the underlying stochastic processes have to be considered, that is solved by considering historical production data. Therefore, the objective is to define how to assemble a certain product variant with a given number of operators to minimize the losses and balance the workload of the operators instantly applying the preprocessed historical dataset.

3. SOLUTION APPROACH

At most companies, production planning and scheduling processes are supported by an enterprise resource planning (ERP) system, which can handle the integrated information and material flow as well as the corporate level planning activities. However, they often fail to perform the line-level control tasks, as for example the calculation of the proper operation control and usually, these problems are solved manually by the production planners or shift leaders based on their experience. In order to define a production planning method that combines the capacity control with the mid-term planning efficiently, the co-operation between the logical and physical layers of the production system must be ensured. This means that the mathematical model has to rely on the production log data that reflect the real work contents, instead that of the norm times that are predefined for each product. The notation used in the prediction and planning models is summarized in Table 3.1.

3.1 Define the capacity control policies

In order to determine the proper operator-task assignments for each product and all the possible number of operators, a discrete-event simulation (DES) tool is applied. Even though state-of-the-art assembly lines are usually equipped with advanced sensor network, the real workload of the operators is hard to monitor. A detailed DES model of the assembly line can provide reliable results about the utilization and several various control policies can be evaluated. The main advantage of using simulation for such purposes is its capability to include the stochastic nature of important processes. For the validation of the simulation model, sensor-level as well as MES data is used that reflect the real processing times, the production rates and personnel.

Besides the simulation of the historical production, several random generated but possible operator control scenarios are analyzed. The input parameters of the simulation are the number of the operators and the assignment of the operators to different tasks. In order to define the best policy for each product variant, only one variant is produced in each scenario. The main output of the simulation analysis are the utilization of the operators and the performance of the line.

Table 1. The applied notation

Sets	
N	the set of production orders
P	the set of products
T	the set of working shifts
Variables	
x_{it}	production of order i in shift t (binary)
y_{pt}	production of product p in shift t (binary indicator variable)
q_{pt}	produced volume from product t in shift t (integer)
w_t	number of operators working in shift t (integer)
Parameters	
p_i	product of order i
v_i	volume of order i [pcs.]
d_i	due date of order i [shift]
h_i	inventory holding cost of order i [cost/order/shift]
l_i	late delivery cost of order i [cost/order/shift]
c_{it}	deviation cost of order i in shift t
s	duration of a shift
r	cost of a setup
k	cost of an operator per shift
w^{\max}	the max. number of operators working in the same shift
$Q(\bar{q}_t)$	overall manual time requirement in shift t [minutes]

3.2 Prediction of real capacity requirements

In case of paced or highly automated assembly lines the capacity requirements can be represented with deterministic values, as their variability is rather low. As already mentioned in the introduction, in case the line is unpaced, moreover, the number of workers is less than the number of workstations, the capacity requirements cannot be represented reliably in a general way. Stochastic optimization can be applied in that cases, however, this require high computation efforts and special solver algorithms. Additionally, diverse reject rates of the product variants and the varying amount of rework also increase the complexity of the planning models.

In order to tackle these problems, in our approach a production planning model is introduced that determines the near optimal production plan and the number of human operators simultaneously, even besides the above mentioned factors. The essence of the method is the introduction of the capacity requirements as a general function of the products produced in the same shift. These functions can be approximated by regression models and can be integrated directly in the production planning calculation.

In order to approximate the real capacity requirement of a given production lot mix assigned to the shift ($Q(\bar{q}_t)$), a multivariate linear regression model is proposed. The efficiency of applying regression models for capacity planning in an uncertain environment was shown by the authors in Gyulai et al. (2014a,b). The input variables of the regression are the volumes of the products assembled in the same shifts (q_{pt}), and the output is the total manual time that is required to assemble the products. The regression models are defined by historical data gathered from the SCADA (supervisory control and data acquisition) system of the assembly line. The regression function is defined as follows:

$$Q(\bar{q}_t) = \beta_0 + \sum_{p=1}^P \beta_p q_{pt}. \quad (1)$$

By this way, the real capacity requirements (including rework rates, machine downtimes operator movements and capacity control policy effects) of the set of orders assembled in the same shift can be estimated. The function can be integrated in the aggregate production planning model, which is described in the following section.

3.3 Production planning model

The core of the production planning is formulated as a mixed-integer programming problem including the capacity requirement function, as well as the other constraints like the order due dates and inventory holding costs. The decision variables of the model give the number of allocated operators for each shift (w_t), the number of setups (y_{pt}), the assembled volumes of products per shift (q_{pt}) and the production of the orders (x_{it}). The model minimizes an objective function that is the sum of the deviation (early delivery and holding), setup and personnel costs (2).

minimize

$$\sum_{i=1}^N \sum_{t=1}^T c_{it} x_{it} + r \sum_{p=1}^P \sum_{t=1}^T y_{pt} + k \sum_{t=1}^T w_t \quad (2)$$

subject to

$$\sum_{t=1}^T x_{it} = 1 \quad \forall i \quad (3)$$

$$x_{it} \leq y_{pt} \quad \forall t, p = p_i \quad (4)$$

$$q_{pt} = \sum_{i=1}^N x_{it} v_i \quad \forall t, p = p_i \quad (5)$$

$$w_t s \geq Q(\bar{q}_t) \quad \forall t \quad (6)$$

$$w_t \leq w^{\max} \quad \forall t \quad (7)$$

$$x_{it} \in \{0, 1\} \quad y_{pt} \in \{0, 1\} \quad w_t \in \mathbb{Z}^+ \quad (8)$$

$$c_{it} = \begin{cases} h_i(d_i - t) & \text{if } t < d_i \\ l_i(t - d_i) & \text{otherwise} \end{cases} \quad (9)$$

The constraints include the fulfillment of all customer orders (3), the calculation of the setups (4) and volumes (5), the capacity restrictions (6)(7) as well as integrity constraints (8). Equation 9 defines the extra cost of the late delivery and inventory holding. The resulting production plan specifies the required number of operators over the horizon, gives the assignment of the customer orders to the production shifts.

3.4 Implementation of the method

The method is evaluated within a software framework that is able to couple various modules developed for various planning and control purposes. The framework is called Simulation and Navigation Cockpit, and developed for increasing the robustness of the plants and supply networks by applying state-of-the-art solutions. The software has a central database that provides the integrated data storage and acquisition among the planning module, the simulation and the graphical user interface (GUI). The proposed method is implemented in the framework by applying a loop-based work flow (Figure 1). The capacity control loop use the sensor network data and the artificially generated scenarios to determine the proper control policies and the utilization of the resources. In the production planning loop, regression models are built over the simulation results, and they are integrated in the production planner module that implements the MIP model. The whole procedure can be controlled via the web-based graphical user interface of the framework.

4. EXPERIMENTAL RESULTS

The efficiency of the combined production planning and capacity control method is demonstrated by an industrial use-case.

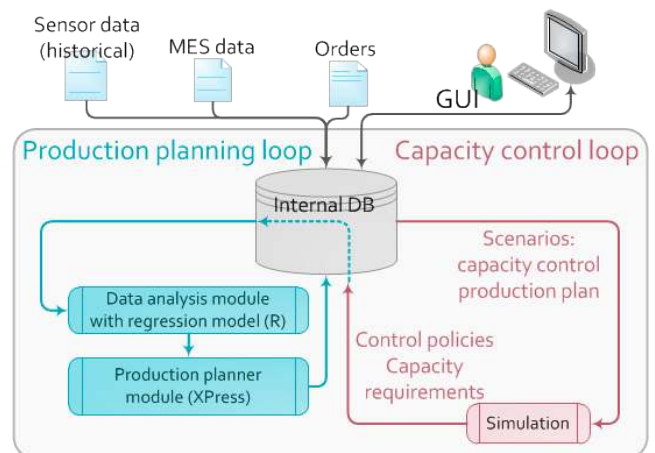


Fig. 1. Implementation of the method in the Simulation and Navigation Cockpit

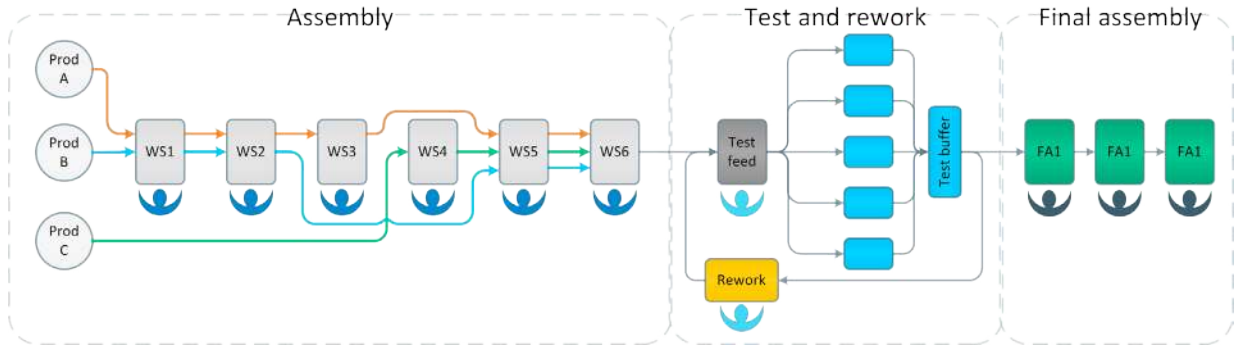


Fig. 2. Schematic of the assembly line

4.1 The characteristics of the assembly line

The target system is a flexible assembly line of an automotive supplier. The line consists of manually operated workstations, an automated testing machine with five slots, final assembly stations and a rework station (Figure 2). In the line, three product families (A,B,C) are produced, each family has several variants. The total number of product variants produced on the line is approximately 150 and the diversity of the yearly volumes is rather high. The line operates three shifts per day, currently the average number of setups is 6-8 per shift. The reject rates of each product type are distinct, therefore, it is important to balance their effects with adjusted production sequence and the corresponding capacity control. To ensure the reliability of the resulted plan, sensor-based process monitoring provides a large amount of data about processing times, setup times, and throughput.

4.2 Simulation and capacity control

In order to determine the best capacity control policies of the product variants, all combinations of the possible input parameters were analyzed in the simulation module. The result of this step is a $p \times w^{\max}$ matrix, containing the operator-task assignment that resulted the highest throughput and least idle times for each p and w_t .

4.3 Prediction of the capacity requirements

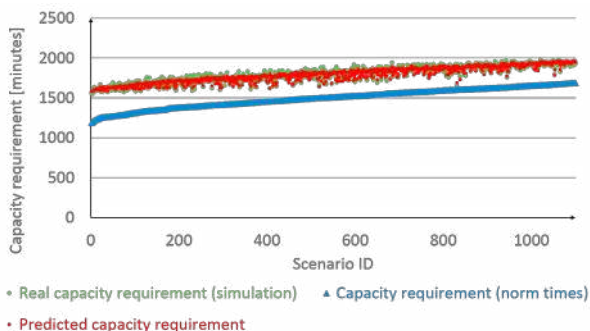


Fig. 3. Results of the multivariate regression

The multivariate regression for the approximation of the capacity requirements was computed using the R statistical environment, by applying its general linear regression function, which took less than 1 second. The regression

model was built over a historical dataset with 1728 shifts, that was split up into a training (576 shifts) and test (1151 shifts) set. As for the input variables, the regression is based on nine product variants (with the highest yearly volumes) that are the most significant variables according to the significance test (each product family is represented by one candidate product). According to the results, the multivariate linear model provides precise prediction for the real capacity requirements: $R^2 = 0.937$, and for all p values, $p < 2 \cdot 10^{-16}$. It is also important to note that the real capacity requirements are significantly higher than the ones calculated according to the capacity norms and applied in the general production planning tools. The reason for the difference are the stochastic nature of the underlying processes like the machine downtimes, reject rates and processing times (Figure 3).

4.4 Production planning and capacity control of the line

The above regression model can be applied directly in the production planning model that was implemented in FICO Xpress and solved by its default branch and bound method. The optimization algorithm was run until an optimality gap of at most 2% was achieved, which required 280 seconds on average. In the experimental case, a fixed-horizon planning problem was investigated, and solved by the current norm-time based planning as well as with the improved, regression-based model. The input of the production planning was 357 production orders concerning nine products with the highest yearly volumes. The horizon of the planning was 20 days, the due date of the orders were given in production shifts from 1 to 60.

In the first case, the planning was done based on the currently applied norm times, and the resulted plan was executed in a simulation environment in which stochastic effects were also included. The execution of the plan resulted in a significant amount of backlogs—due to the capacity shortages—that means 907 products were not assembled and delivered in time (Table 2).

In the second case, the capacity constraints in the model were represented by equation 6, the rest of the planning model left unchanged. According to the simulation results, the improved planning model resulted in a production plan that is more robust against the negative effects of reject rates, as the amount of backlogs was decreased to 106, and the objective function value—including the deviation, operator and setup costs—also much less than in the previous case.

An important fact that these results were achieved by proper sequencing that can decrease the negative effects of the rejects rates, and not by simply increasing the norm times and thus the allocated capacities as well. Moreover, the number of working shifts ($\sum_{t=1}^T w_t$, $s = 480$ minutes) is decreased from 290 to 240 that is a positive ‘side effect’ of the regression-based planning (Table 2 and Figure 4.4). Comparing the total production costs (objective function value), the regression-based method provides much better results.

Beside the production planning, another important goal is to identify the proper capacity control policies. This task was solved by running the simulation model on a historical dataset with different operator-task assignments. By this way, the best scenarios were selected—for each of the nine products with the highest yearly volumes—and included in the planning problem. In the production plan execution mode of the simulation model, these controls were applied, in order to make the plan even more robust.

Table 2. Comparison of the planning methods

Method	Obj. function	Backlog [pcs.]	$\sum_{t=1}^T w_t$ [shifts]
Current	14 904	907	290
Improved	12 467	169	240

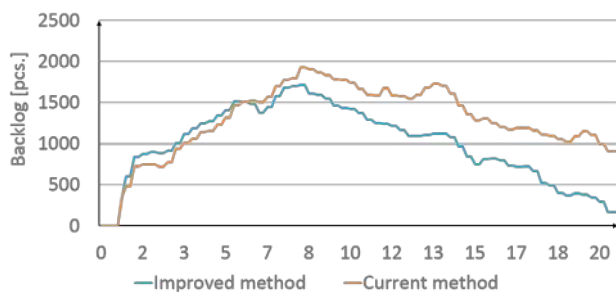


Fig. 4. Execution of the plans: the amount of realized backlogs along the planning horizon

5. CONCLUSION

In the paper, a robust, regression based aggregate planning method was introduced that is aimed at providing feasible production plans that face with changes and disturbances occur during the production. The method is based on a multivariate-regression to estimate the capacity requirements of the orders that are assigned to the same production period. The method relies on historical data gathered from the SCADA system providing reliable capacity estimation that include the stochastic parameters like the downtimes, varying rework rates occurred by the rejects and the stochastic processing times. The capacity requirements were represented by a multivariate linear function that can be integrated directly in the mathematical model of the aggregate planning model. By this way, the production (order-shift assignment) and shift planning is done simultaneously. By introducing additional constraints in the model, special requirements like pattern-based shift planning can be solved, considering the company-specific planning requirements. The efficiency of the planning method is proven to be robust against the

reject rates by evaluating its feasibility with discrete-event simulation.

As for the future work, the primary aim is to generalize the planning method to be able to apply it for different types of assembly system. Another important goal is to define a self-building modeling framework that applies uniform data structure to build-up the simulation model of the systems simultaneously with the corresponding mathematical models in order to ensure their co-evolution and validation.

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