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# Capacity analysis and planning for flexible assembly lines

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*Abstract:* In today's competitive industry, flexible flow assembly lines are one of the most efficient solutions to respond the customer expectations such as the high variety of the products and short lead times. In the paper, a comprehensive method is proposed to analyze the key performance indicators of a flexible, automotive assembly line, especially those that measure the utilization and load of the machine resources as well as the human operators.

The proposed method is generally based on the analysis of real data provided by the sensor-based monitoring system of the assembly line, and the mixed-integer production planning models defined according to the performed analysis. The results of such data analysis can be embedded in mathematical programming models for robust production planning. The production planning process can be performed on a rolling horizon basis by applying real production data that provide more reliable results.

The result of the proposed capacity planning method is a production plan that determine the optimal volume of products to be assembled in each shifts and the optimal number of human operators assigned to the production lines. The novelty of the proposed method is manifested by the direct integration of statistical learning methods like multivariate regression and prediction in mixed-integer optimization methods

*Keywords*: production planning, capacity planning, statistical learning

## INTRODUCTION

In the automotive industry, competitive market conditions, high variety in the products and shortened lifecycles are the main drivers when discussing production planning topics, that is a general decision making process on the acquisition, utilization and allocation of production resources to satisfy customer requirements. Typical planning decisions include the identification of work force level, production lot sizes, assignment of overtime and sequencing of production runs [4]. The activities of production planning are generally described by a three-level decision making hierarchy: based on the time horizon and the level of aggregation; strategic, tactical and operational (control) levels are identified [2]. The paper focus on the tactical level planning that is responsible for determining the production lot-sizes, the corresponding material requirements and inventory levels for every planning periods (e.g. shits). In the industrial practice, capacity requirements are usually planned simultaneously with the production, since they have the same planning horizon and the planning constraints and objective functions are interlinked.

In order to cope with varying demands and high product variety, automotive companies usually applies flexible assembly systems like flexible flow and mixed-model lines. After performing the required setups, flexible flow lines are capable of producing different product varieties in batches. Considering the manually operated flow lines, the number, workload and utilization of the operators and thus the throughput of the line is highly influenced by the adopted production plan.

In the paper, a comprehensive method is proposed to analyze the key performance indicators of a flexible, automotive assembly line, especially those that measure the utilization and load of the machine resources as well as the human operators. Based on the analysis, an aggregate production method is defined that determine the optimal lot sizes and required workforce. In order to adjust the production rates to the work regulations, a pattern-based shift planning model is proposed that provide the optimal balance between capacities and production volumes.

## ROBUSTNESS IN PRODUCTION PLANNING

Classical planning approaches usually rely on deterministic planning information and fail to cope with a dynamic environment and the considerable uncertainty of the underlying planning information. In order to face the challenges resulted by changing environments, robust techniques are required that provide feasible production plans. Robustness in production planning involves refined approaches that aim at handling predictable or unpredictable changes and disturbances. They react 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) [17]. In order to reach robustness, stochastic programming and robust optimization is usually applied addressing uncertainty of relevant parameters [14]. A production plan is termed robust in case it performs well even after a disruption. On the other hand, a plan which tends to perform well after even after replanning is called flexible [10].

In our methodology, robust planning is the logical layer of the robust production. It is a decision making process, providing feasible production plans that consider predictable changes (i.e. fluctuation of order stream), and stay feasible and stable even after an unpredictable event (i.e. machine breakdown) occurs, and need to provide proactive as well as reactive approaches. A general plan given by classical, deterministic planning methods is only efficient if we well-understand the causal relationships of the system based on which we can build a formal model to predict its behavior. Moreover, the plant should be entirely controllable, in order to get fully implementable deterministic plans [7]. The robustness of the systems often works against other efficiency criteria, hence, means a natural trade-off. Further ways of taking uncertainties into account, and to achieve more robust solutions are to either apply stochastic models [3] (e.g., by estimating the underlying stochastic processes), or using adaptive and cooperative approaches which allows prompt responses to changes and disturbances [8].

## PRODUCTION PLANNING FOR FLOW ASSEMBLY LINES

Medium-term production planning (tactical planning) and lot-sizing has a broad literature and wide range of efficient solution methods. The most fundamental way of defining these problems is applying mixed-integer programming (MIP) that can be solved by systematic algorithms (e.g. branch and bound) or heuristics, even though the *NP*-complete nature of the problems. The lot-sizing problems –in contrast with short-term scheduling– are formulated in discrete time, meaning that the planning horizon is subdivided into a set of fixed-length time slots, thus the problems can be described by MIP models. Beside the time representation, another important reason for describing the problems by this way is the existence of features like setup costs, setup times and machine assignment decisions [11]. Despite the efficiency of the solver algorithms, large scale problem instances are still hard to solve in a reasonable time that is a general requirement at most of the companies.

Considering the aggregate models for the flow assembly lines, the typical problem is to determine the volume of products to produce in each time period considering a fixed planning horizon (usually some weeks divided into shifts) and a deterministic, discrete demand volume per product and period [12]. Due to the interdependencies among production planning and scheduling problems of the flexible flow lines, they are often combined with each other [6][13][15]. In case production and workforce planning are combined in the same model, the general objective is to minimize the total production costs concerning a certain period. The objective function is usually composed of the salary of the operators, the cost of inventories, tardiness and setups [9][16].

## STATISTICAL LEARNING MODELS

Despite the efficient solutions for the deterministic problems, the calculated plans are often tend to be unfeasible, due to the stochastic nature of the parameters (e.g. processing time variability) and the occurrence of disturbances during the production (e.g. machine breakdowns). These factors are usually ignored in most of the models, however, their effect on the resulting plan might be significant. In order to cope with this, the paper introduce a method that combines statistical learning with mathematical optimization.

Basically, statistical learning refers to a set of tools for understanding and learning from data, and provides solutions to understand the correlations among parameters and processes. Though the term statistical learning is fairly new, many of the concepts that underlie the field were developed long time ago [5]. There are two main classes of these tools: the supervised and unsupervised learning techniques. The supervised learning is aimed at predicting some output parameters based on the input parameters and the priori known training set. The most fundamental supervised learning tools are the linear regression models that are capable of accurately predict a value of a quantitative output variable $Y$ assuming that there is approximately a linear relationship among the input variables $X_1 \dots X_p$. In this case, the regression models has the following form [5]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p + \varepsilon$$

We interpret $\beta_j$ as the average effect on $Y$ of a one unit increase in $X_j$, holding all other predictors fixed –known as the intercept term–, and $\varepsilon_0$ is the error term. Although linear regression models may seem overly simplistic, they are extremely useful in many of the practical cases, and can outperform more sophisticated models and usually have higher computational requirements.

Other effective but simple techniques for practical applications are the tree-based methods that can be used for regression and classification as well. The general idea behind these methods is the partition of the feature space into a set of disjoint rectangular regions, and fit a simple model in each one [5]. Building a regression tree over a given dataset is composed of two general steps. First, the feature space is divided into a set of disjoint regions, then for every observation which falls into a certain region the same prediction is made that is the mean of the region.

## PROBLEM FORMULATION

The considered production planning problem is defined as it follows. Given a manually operated, flexible flow assembly line that is capable of producing a set of identical products. The line is built-up by a set of manually operated sequentially coupled workstations that realizes a linear material flow. The operation mode of the line is one-piece flow and working 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, and the assembly tasks have to be performed under a product-specific takt time. At the end of the line, an automated testing station checks the quality of the products. 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 put in the testing station again.

As for the production planning problem, the customer orders for the products are available for a certain planning horizon that is split up into a set of time buckets (shifts). Each customer order can be characterized by an order volume and a due date. Make-to-stock option is available in every time bucket, therefore in case of capacity shortage, orders can be fulfilled from stocks, however, holding inventory is associated with extra costs. Order fulfilment after the due date is possible (backlog) but also penalized with extra costs. The decisions also involve the allocation of the capacities in particular the personnel, the production sequence and balancing the inventory levels with production and supply. The goal is to define a robust mid-term production plan that is able to cope with changes and disturbances that occur in the everyday production. Further purposes of the method is to provide an optimal plan that is based on the minimization of the production costs on a certain horizon, increase the utilization of the capacities (machines and human operators) and provide pattern-based shift schedule. In the paper, the following notation is applied:

| | |
|---|---|
| $N=1...n$ | set of customer orders |
| $P=1...p$ | set of products |
| $T=1...t$ | set of time buckets |
| $L_i$ | due date of order $i$ |
| $l_i$ | inventory holding cost of order $i$ |
| $p_i$ | product of order $i$ |
| $v_i$ | delivery cost of order $i$ |
| $c_{it}$ | deviation cost of order $i$ in shift $t$ |
| $Q_t(p)$ | capacity requirement function |
| $s$ | length of a shift |
| $r$ | cost of a setup |
| $w$ | cost of an operator per shift |

## SOLUTION APPROACH

At several companies, the production planning processes are supported by manufacturing execution systems regarding the order management and material requirements planning (MRP), however, that planning process focuses more on the whole production facility, including all assembly lines. The “local” production planning and execution of the assembly lines concerning the sequencing and job releasing is generally done by the production planners manually applying spreadsheets and local databases. In order to develop a production planning method as described above, the efficient co-operation between the logical and physical layer 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 pre-defined for each product (Figure 1).

## REGRESSION MODELS

A general difference from the general lot-sizing models is in case of paced (e.g. with conveyor belt) assembly lines, the available and required capacities can be given easily in the takt (cycle) times. In case the line is unpaced, moreover the number of workers is less than the number of workstations, the capacity requirements cannot be represented in a general way. In these cases, additional parameters are required that enlarge the problem sizes and require high computation efforts.

Additionally, diverse reject rates and the rework option also increase the complexity of the planning models due to the fact that the capacity requirements cannot be considered in a traditional way.

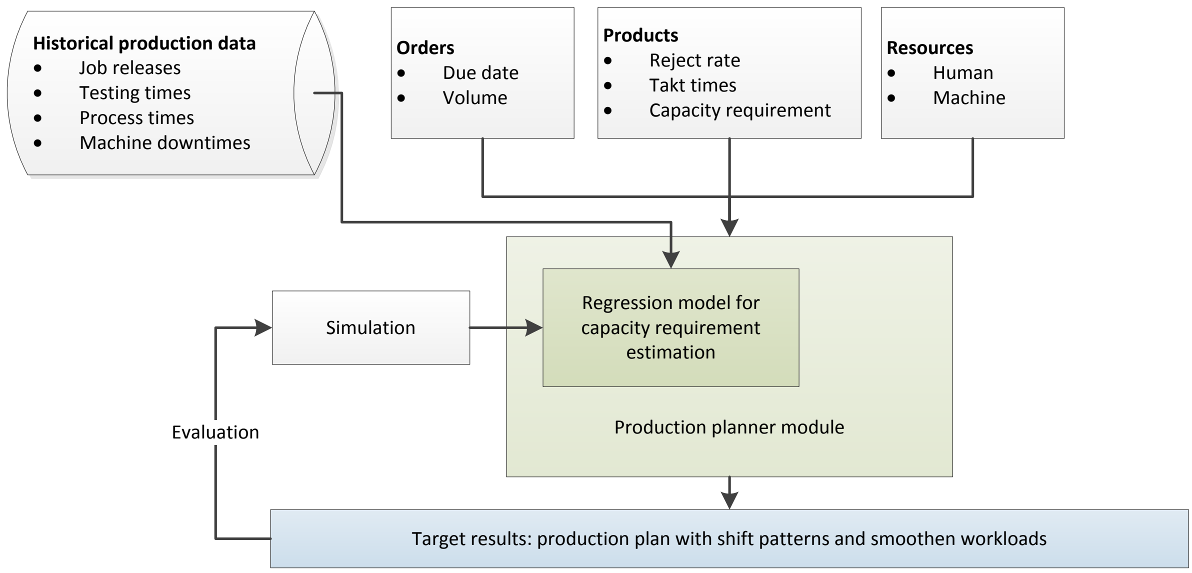


Figure 1: Work- and dataflow of the production planning method

To tackle these problems, an aggregate planning model is introduced that determine the optimal production plan and the number of human operators simultaneously even besides the above mentioned factors by introducing the capacity requirements as a general function of the products produced in the same time bucket. These functions can be approximated by statistical learning methods (regression), and can be embedded in the planning models.
In order to approximate the real capacity requirement of a given order set assigned to the same time bucket *($Q_t(p)$)*, a multivariate linear regression model is combined with the production planning model. The input variables of the regression are the volumes of the products assembled in the same shifts, and the output is the total time that is required to assemble the order set. 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 it follows:

$$Q_t(p) = \beta_0 + \sum_{p=1}^{P} y_{pt} \cdot \beta_p \,, \tag{1}$$

where $y_{pt}$ is the volume of product $p$ assembled in $t$.

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.

## PRODUCTION PLANNING MODEL

The aggregate production planning problem is formulated as a mixed-integer programming model that include the capacity requirements defined in the previous section as well as the other constraints like the due dates, inventory holding costs and the pattern based shift model. The decision variables give the assignment of the orders to the identical shifts, the number of setups and the number of operators working simultaneously. The objective is to minimize the total production costs on a fixed horizon, including the operation and personnel costs (Eq. 2.).

Decision variables:
$x_{it}$ production of order $i$ in shift $t$
$y_{pt}$ production of product $p$ in shift $t$
$h_t$ number of operators working in shift $t$

$$c_{it} = \begin{cases} l_i(L_i - t) & \text{if } t < L_i \\ v_i(t - L_i) & \text{if } L_i \geq t \end{cases}$$

$$\min \sum_{i=1}^{N}\sum_{t=1}^{T} x_{it}c_{it} + \sum_{p=1}^{P}\sum_{t=1}^{T} y_{pt}r + \sum_{t=1}^{T} h_t w \tag{2}$$

subject to

$$\sum_{t=1}^{T} x_{it} = 1 \tag{3}$$

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

$$h_t s \geq Q_t(p) \quad \forall \text{ t} \tag{5}$$

$$h_t = h_{t+3} \quad \forall \text{ t} \tag{6}$$

$$x_{it} \in [0,1], \text{ y}_{\text{pt}} \in \mathbf{R} \quad \forall i,t \tag{7}$$

The constraints include the fulfilment of all customer orders (3), the calculation of the setups (2) as well as the capacity restrictions (5). The pattern-based shift model ensure that the same number of operators are working in the same shift day-by-day (6). The resulting production plan specifies the required number of operators over the horizon, and give the assignment of the customer orders to the production shifts.

**EXPERIMENTAL RESULTS**

In order to demonstrate the capabilities of the regression-based production planning model, an industry-related dataset is applied. The analyzed production system is a flow assembly line consisted of manually operated workstations, an automated testbench with five slots, final assembly stations and a rework station. On the line, four product families are produced with several product 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 two or three shifts per day, the daily shift sequence is also driven by the customer orders and the average number of setups is 6-8 per shift. The reject rates of each product type are distinct, therefore, a proper production planning method should be able to balance the reject rates of the products with adjusted production sequence and capacities allocated e.g. by determining shift patterns. To ensure the robustness of production planning, sensor-based process monitoring provides a large amount of data about process times, setup times and throughput.

The multivariate regression for the approximation of the capacity requirements was computed using the *R* environment, by applying its general linear regression function, which took ca. 2 seconds. The regression model was built over a historical dataset with 1500 shifts, that was split up into a training and test set. As for the input variables, the regression is based on the top four runner products that are the most significant variables according to the significance test (each product family is represented by one candidate product). The results of the model fitting are the followings (Eq. 8.):

$$Q_t(p) = 1428 + 1{,}438 p_1 + 1{,}327 p_2 + 1{,}59 p_3 + 1{,}698 p_4 + \varepsilon \tag{8}$$

The above function was integrated in the aggregate production planning model that was implemented in FICO Xpress and solved by its default branch and bound method. The input of the production planning were 180 shifts (a roughly two month horizon), 43 products and 391 customer orders. The capacity requirements of the products from the same family were equal, however, other parameters like the hold and delivery parameters were different. The optimization algorithm was run until an optimality gap of at most 7% was achieved, which required 308 seconds on average.

*adjusted $R^2$= 0,889*
*p-values < 2e-16*

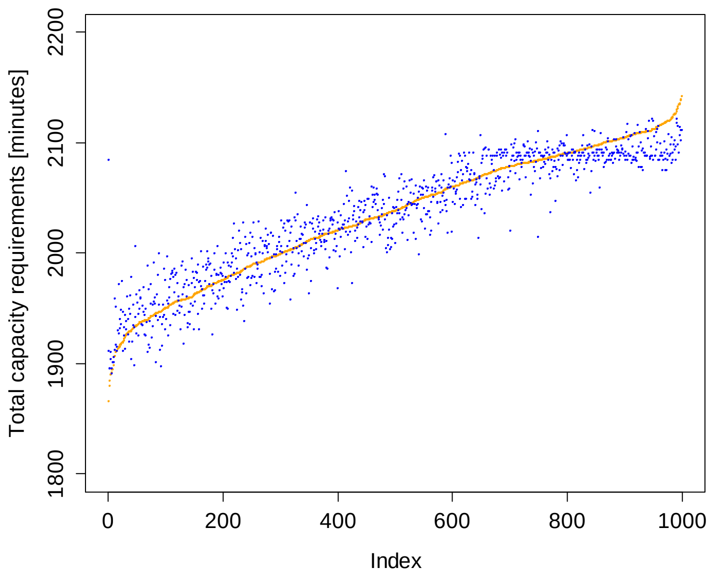


Figure 2: Results of the multivariate regression

The feasibility of the calculated plan was evaluated by applying discrete-event simulation, considering all the relevant stochastic parameters e.g. the reject rates, processing times and machine downtimes. The simulation results shown that the regression based capacity and production plan is robust enough to cope with those uncertainties, and the plan stays feasible even in besides unpredictable events.

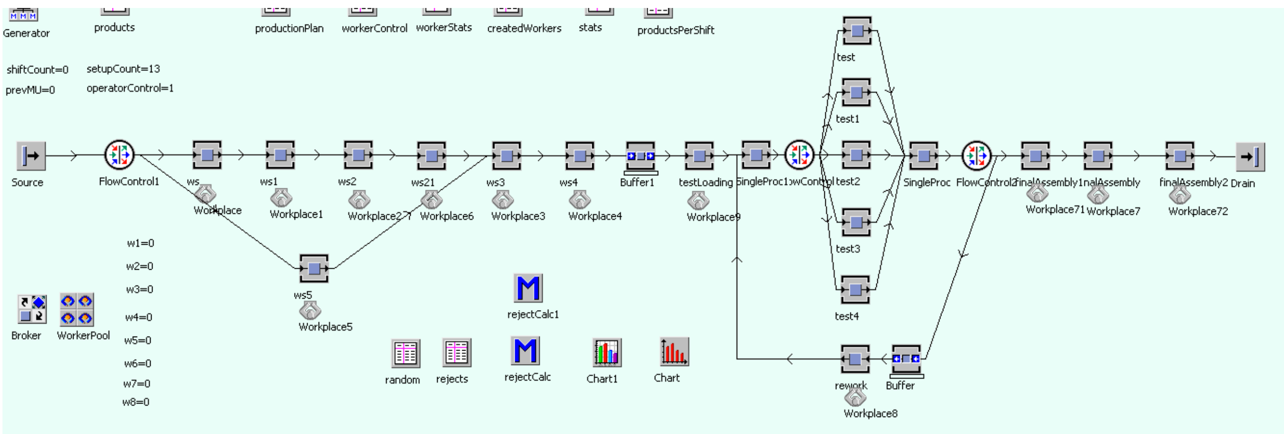


Figure 3: Interface of the discrete-event simulation model

## CONCLUSIONS AND FUTURE WORK

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 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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