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Assignment of Customer-Specific Orders to Plants with Mixed-Model Assembly Lines in Global Production Networks

Jens Buergin[a]*, Philippe Blaettchen[a], Chuanqi Qu[a], Gisela Lanza[a]

[a]*wbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), Kaiserstrasse 12, 76131 Karlsruhe, GERMANY*

* Corresponding author. Tel.: +49-721-608-44013; fax: +49-721-608-45005. *E-mail address:* Jens.Buergin@kit.edu

Abstract

Build-to-order series production is gaining increasing importance as markets demand customer-specific product variants. Orders have to be assigned to plants and periods in global production networks and then to lines and cycles. Consequently, respective workloads as well as supplied materials have to be balanced due to limitations in resource capacities.
As first step planning defines the solution space for second step planning, this paper introduces a mathematical model for order assignments to plants and periods anticipating assignments to lines and cycles. Given that orders are not fully specified for first step planning, the approach includes provisions for dealing with uncertainty.

Keywords: Global Production Networks; Order Planning; Hierarchical Planning; Mixed-Model Assembly Lines

1. Introduction

The importance of customizing products to satisfy individual customers' demands has been increasing significantly throughout the last decades. [1] Kotler argues that mass markets no longer exist and that even segmented markets are too broad, making it necessary to consider the demands of individuals. [2] This development can be noted specifically when regarding the idea of mass customization, which emerged during the late 1980s. Mass customization, which can be defined as a system for the production of output that meets individual customer needs at a cost close to what is achievable in mass production, has gained increasing importance. [3]

There are a number of levels at which customization can take place. In many important cases, e.g., the production of automobiles, standardized modules are assembled to achieve customized products. In this case, often termed build-to-order (BTO), development and production of components is based on demand forecasts, while final assembly is based on customer orders. [4] To be able to achieve high volumes of output at competitive prices, while at the same time remaining able to fulfill specific customer demands through the individual assembly of components to products according to customers' specifications, mixed-model assembly lines (MMAL) are used. [5] These are assembly lines in which flexible resources are utilized in order to reduce set up effort and achieve sequences of products with lot sizes of one. [6] MMALs can be found in a wide range of industries, from consumer electronics to aircraft manufacturing. [6, 7]

While the importance as well as the capability to produce customized products has increased, so has the prevalence of global production networks, in which business activities are distributed throughout multiple countries. [8] Of great importance in such networks are final assembly activities; locating these within the markets which they serve can improve delivery lead times and lead to considerable savings in transportation costs and tariffs. [9] Consequently, and due to the necessity of employing sufficient capacity, globally operating companies are likely to devote a range of plants to final assembly activities.

Assuming a global production network in which the final assembly of mass-customized products is managed by MMALs in a range of plants, different planning tasks need to be considered. Firstly, specific orders traceable to customers have to be assigned to plants as well as to periods for final assembly in one planning step, as both assignments are necessary for

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material requirements planning. Within the plants and periods, each order needs to be assigned to one of a range of assembly lines as well as to a cycle within that line, i.e. the orders need to be sequenced. These two assignments may also be conducted in a single step, as the assignment to cycles requires the assignment to lines and an assignment to lines prior to the assignment to cycles is unlikely to be necessary.

However, the latest possible time for planning both steps, covering spatial and temporal assignments each, differ. The first planning step may be described as tactical or mid-term, while the second planning step may be described as operational or short-term. It should be noted, however, that it is difficult to establish any clear definition of the terms independently from specific industries and sometimes even from specific planning objects [5, 9].

Due to the differences in planning lead times, the two planning steps should be considered sequentially in a hierarchical approach. This allows for reduction in complexity of planning. Furthermore, it is likely that different organizational levels are responsible for carrying out mid-term decisions concerning all plants than the ones that are responsible for carrying out short-term decisions concerning individual plants. Planning is probably more effective if decision-making is allocated to the appropriate level. [10] To reflect this, the term global order assignment is used for the first planning step and the term local order assignment is used for the second planning step.

Global order assignment defines the solution space for local order assignment, with lines being a subset of the plants and cycles being a subset of the periods that orders can be assigned to in global order assignment.

A distributed order freeze is assumed, where each option of an order is specified at the latest possible point in time considering replenishment lead times of individual parts. [11] Global order assignment needs to be conducted under uncertainty if there are unspecified options at the time of execution. Furthermore, global order assignment has to anticipate local order assignment in order to make plans robust.

Within the context of this work, literature on the assignment of orders in such a set-up is first reviewed. Following this, an approach to model global order assignment with anticipation of local order assignment, as well as the model application, are introduced. The paper is concluded with a summary and an outlook on further research.

2. Literature review

2.1. Order assignment to cycles in MMALs

In the context of MMALs, mostly two planning problems are considered. Firstly, the resources necessary at such an assembly line need to be grouped and assigned to stations. This is called line balancing. Secondly, orders need to be assigned to production cycles, which is called sequencing. [5] The sequencing of MMALs will be anticipated in the global order assignment, as described further below. Two basic objectives for the sequencing of a MMAL can be identified in literature: minimization of work overload and balancing of material requirements. [6, 12]

Options are often used to define a product in a way so that it meets the specific needs of a customer. [3] The options chosen for one order through configuration lead to processing times specific to the order. If several time-intensive orders are built consecutively on a MMAL, stations may become overloaded which then needs to be dealt with, e.g., through compensation or line stoppage [5]. The mixed-model sequencing (MMS) approach takes into explicit consideration processing times, worker movements and other characteristics of the MMAL. Based on this, work overloads caused by the choice of a sequence are minimized. [6] With the car sequencing (CS) approach, less information and simpler computation is required. Instead of explicitly considering processing times, certain spacing constraints are prescribed, i.e. at most H out of N orders that can be processed consecutively on a MMAL can be fitted with a certain option. As can be derived from its name, CS is predominant in the automotive industry. [12]

The options chosen within one order also imply certain material requirements. The second objective leads to a focus on balancing the requirements of materials in assembly throughout the planning horizon. Steady demand is one of the prerequisites to profit from a JIT supply system. Level scheduling (LS) forms the only corresponding approach. Here, sequences for MMALs are built by minimizing the deviation from an ideal material requirement rate. Other approaches to LS also exist, that consider throughput or output instead of input. However, these are not addressed in this paper. [6, 13]

In some instances, the approaches are combined to achieve improved sequencing results. The way in which combination takes place depends on model specifications. [14, 15]

2.2. Order assignment to plants or periods

Bruns and Sauer develop an approach for scheduling orders for a number of plants. Each order, in this case, is processed at multiple plants. To coordinate global and local planning levels, predictive and reactive scheduling is applied and combined. The actual approach for solving the scheduling problems on both levels is not focused here, however. [16] Chen and Hung formulate a model and an algorithm to allocate orders to multiple plants. [17] Similarly, Chan et al. focus on the allocation of orders to factories and the computation of schedules at each factory, which, individually, represent job shops. Orders are not reallocated between factories, which is explained by economic reasons and a lack of capability. The allocation and scheduling problems are solved simultaneously, which implies that all characteristics of orders are known at the time that they are allocated to plants. [18] The above authors, however, neither specifically consider plants with MMALs as the destination for assignment, nor the variety in demand that is associated with mass customization.

The level of information is likely to increase over time, implying that more information is available for the second planning step than for the first. This makes it necessary for global order assignment to anticipate specifications of orders as well as local order assignment in order to avoid myopic decision-making. [4] In a hierarchical planning system, Schneeweiss differentiates between four types of anticipation. Firstly, perfect anticipation implies that the actual behavior of the lower planning level is fully known and considered. Secondly, approximate anticipation also considers the behavior of the lower planning level, although only in an approximate way. Thirdly, implicit anticipation only considers part of the lower planning level's behavior. These three types of anticipation are called reactive. In contrast, with non-reactive anticipation, only basic characteristics of the lower planning level are considered, which do not react to the upper planning level results. [19]

Dörmer et al. consider the problem of assigning orders to planning periods during which those orders are then sequenced to cycles of an MMAL. They develop a number of solution approaches that anticipate the performance of sequencing with the orders given. Furthermore, they propose an integrated approach that directly sequences all orders when allocating them to periods in a MMS approach. They find this integrated approach with perfect anticipation to provide superior performance. [12] This implies, however, that orders are fully specified by the time that planning takes place.

In contrast to Dörmer et al. [12], Wittek, who develops a model to assign production volumes to plants in the automotive industry, assumes demand to be completely unspecified at the time of planning. Instead of specified orders, only basic product models are assigned, for which demand is known sufficiently in advance. Even though MMALs are used for final assembly, it is assumed that capacity utilization of any model is equal. [9] This makes consideration of the impact of the later chosen sequence on work overload superfluous. Furthermore, material balancing is not considered, only aggregated capacity constraints for materials are taken into account. Clearly, this shows a case of non-reactive anticipation, where only basic structural information of the lower planning level, e.g., about capacities, is considered in the upper planning level.

Similar to Dörmer et al. [12], Boysen et al. suggest an approach to assign orders to periods in an MMAL environment, which they call master scheduling. This is presented in an overall planning framework that starts with an initial configuration of the MMAL. The master schedule is then generated, after which the MMAL is reconfigured to accommodate for major adjustments in product mix or processing technologies. Both initial configuration and reconfiguration are line balancing tasks. After reconfiguration is completed, the orders are sequenced to the MMAL. Re-sequencing is further considered to accommodate for unexpected disturbances. Due to high interdependence of the master scheduling and the sequencing tasks, the authors suggest ways in which the latter can be anticipated. Different constraints are proposed for the master scheduling model for each form of sequencing (MMS, CS and LS). [5] The anticipation mechanism corresponds to implicit anticipation, as given above. From the perspective of anticipation, the model can thus be seen as being in-between the models of Wittek [9] and Dörmer et al. [12]. Moreover, Boysen et al. claim that LS reduces the degrees of freedom in sequencing more than what is necessary. Accordingly, only few materials are actually delivered to a line in sequence and arrival in bulk at discrete points in time is more common. This makes reduction of inventory through leveling of material input only possible if the periods considered are greater than individual cycles, e.g., when planning at an aggregated level as in the first planning step. [13]

Boysen et al. [5] and Wittek [9] consider minimization of costs and maximization of profit, respectively, as the objective for the assignment. Maximization of profits and often, consequently, minimization of costs is likely to be the objective for a majority of organizations (see, e.g., [20]), which is why choosing this as the goal for mid-term planning is consistent. Minimization of costs is rarely sensible at the lower level of planning, however, because it is difficult to identify the cost drivers and the influence of the sequence upon them at this detailed level [13]. Instead, as in the case of MMAL sequencing, surrogate objective functions are used. Due to the integration of sequencing within the planning model, Dörmer et al. consider work overload as the characteristic to be minimized even for mid-term planning. [12]

2.3. Further considerations

Often, as in the cases of Boysen et al. [5] and Dörmer et al. [12], data is assumed known and constant. In practice, however, uncertainty is common. In particular, when planning where and at what time to produce orders, full specification of those orders in advance is very unlikely. [9] To improve decision-making processes, this uncertainty needs to be considered. Generally, there are a number of ways to do so. Firstly, deterministic values can be replaced with expected values. [21] This is often used, e.g., in scheduling, where it can be seen as an improvement over pure deterministic approaches, but it often is not sufficient. Due to the possibility of two substantially different distributions having the same expected value, it is often necessary to consider the entire distribution of random variables, in which case stochastic optimization models arise. [22] These can further be differentiated between compensation and chance-constrained models with the former including the possibility of compensation in case of constraints being breached and the latter including a certain minimum probability that constraints are fulfilled. Obviously, while solution quality may improve, computational effort increases. [21] Robust optimization allows foregoing knowledge of probabilities, by using scenarios to describe potential realizations. The aim is not a probabilistic guarantee of some kind, but to achieve a solution close to optimality under all scenarios considered. [23]

There is a significant amount of literature on the topic of stochastic or robust scheduling. [22, 24, 25] However, to the best knowledge of the authors, in the context of MMAL, uncertainty is only considered in balancing or combined balancing and sequencing tasks [26-28]. In the context of standalone sequencing of MMAL or in the context of anticipation of those sequences in global order assignment, uncertainty remains to be incorporated. Uncertainty, when considered in the contexts named above, is often constrained to processing times. This is only natural because of the high susceptibility to variance in such settings [28]. Due to processing times being largely dependent on the choice of options in an MMAL context, the uncertainty in options, if existent, needs to be considered foremost before the uncertainty in processing times required to produce those options, however.

3. Proposed approach

Nomenclature

i	order index $(i=1,\ldots,I)$
l	plant location index $(l=1,\ldots,L)$
$\bar{l}$	customer location index $(\bar{l}=1,\ldots,\bar{L})$
t	period index $(t=1,\ldots,T)$
o	option index $(o=1,\ldots,O)$
r	interest rate
$Cost_l^{\mathrm{Pro}}$	production cost for basic product model (not including selectable options) at plant l
$Cost_{ol}^{\mathrm{Pro}}$	production cost for option o at plant l; includes cost for workers, material, etc.
$Cost_i^{\mathrm{Pen}}$	penalty cost per period of delay for order i
$Cost_{l\bar{l}}^{\mathrm{Dist}}$	distribution cost from plant location l to customer location $\bar{l}$
$Time_l^{\mathrm{Pro}}$	throughput time of plant l
$Time_{l\bar{l}}^{\mathrm{Dist}}$	distribution time from plant location l to customer location $\bar{l}$
$Time_{ol}^{\mathrm{Sup}}$	supply time from supplier of option o to plant l
EDT_i	earliest accepted delivery time for order i
LDT_i	latest accepted delivery time for order i
$C_l^{\max}$	maximum capacity (in cycles) of plant l per period
$\frac{H_o}{N_o}$	indication that at most H orders in a sequence of N can use option o
L_o^{CS}	control parameter for anticipation of car sequencing for option o
L_o^{LS}	control parameter for anticipation of level scheduling for option o
α_{lto} resp. α_{to}	control parameters for enforcement of constraints
X_{ilt}	decision variable; binary assignment of order i to plant l at period t
B_{io}	random variable; usage of option o within order i; probability of choice is p_{io}

In the following, an approach is presented to handle the problem of distributing not fully specified orders to plants and periods in which they can be produced on one or multiple MMALs (global order assignment). Similar to Boysen et al. [5], provisions are taken on an aggregate basis to allow for feasibility of generated sequences at a later assignment step (local order assignment). The form of anticipation is implicit, with specific characteristics of lines not considered. It is argued that due to the major influence of the uncertainty considered, the additional model accuracy provided by more exact forms of anticipation is not worth the additional computational effort. Consideration of the impact on local order assignment is thus aggregated over multiple lines and cycles. The approach used is also predictive without reactive components. However, in contrast to Boysen et al. [5], layout of lines is considered to be fixed, implying that line balancing is not necessary. In addition, specification of orders, i.e. option choices, is assumed to be unknown. Rather, binary option choices with known probabilities, depending on the customer of an order, are assumed.

Due to the aggregated nature of the decision making process at this level, only option choices are considered that may critically affect production. Based on the motivation for CS found in literature, it is assumed that only one option of a group of interdependent options has such a critical impact. Consequently, it is presumed that options regarded here are independent from each other:

$$B_{io} \sim Bernoulli\ (p_{io})\ \ \forall i,o \tag{1}$$

where all B_{io} are independent and variables B_{io} that are associated with orders from a certain customer are identically distributed for all orders of the customer.

Following the reasoning given in section 2, the aim is minimization of costs. Revenues and, consequently, profits are not considered, because orders are assumed to be given and requiring of assignment in any case.

$$\min\left(Cost^{\mathrm{Pro}} + Cost^{\mathrm{Dist}} + Cost^{\mathrm{Inv}} + Cost^{\mathrm{Pen}}\right) \tag{2}$$

$$Cost^{\mathrm{Pro}} = \sum_{t\in T}\sum_{l\in L}\sum_{i\in I} X_{ilt} \times \left(\sum_{o\in O} B_{io} \times Cost_{ol}^{\mathrm{Pro}} + Cost_l^{\mathrm{Pro}}\right) \tag{2.1}$$

$$Cost^{\mathrm{Dist}} = \sum_{t\in T}\sum_{l\in L}\sum_{i\in I} Cost_{l\bar{l}}^{\mathrm{Dist}} \times X_{ilt} \tag{2.2}$$

$$\begin{aligned} Cost^{\mathrm{Inv}} = \sum_{t\in T}\sum_{l\in L}\sum_{i\in I} X_{ilt} \times \left(\sum_{o\in O} B_{io} \times Cost_{ol}^{\mathrm{Pro}} + Cost_l^{\mathrm{Pro}}\right) \times r \\ \times \max\left\{EDT_i - Time_l^{\mathrm{Pro}} - Time_{l\bar{l}}^{Dist} - t,\, 0\right\} \end{aligned} \tag{2.3}$$

$$\begin{aligned} Cost^{\mathrm{Pen}} = \sum_{t\in T}\sum_{l\in L}\sum_{i\in I} X_{ilt} \times Cost_i^{\mathrm{Pen}} \\ \times \max\left\{t + Time_l^{\mathrm{Pro}} + Time_{l\bar{l}}^{\mathrm{Dist}} - LDT_i,\, 0\right\} \end{aligned} \tag{2.4}$$

Due to production taking place on MMALs, throughput time is considered constant and independent of orders.

Basic constraints found in (3) and (4) ensure that all orders are assigned exactly to one plant and one period and that no more orders can be assigned to a plant in a period than the amount of production cycles within:

$$\sum_{t\in T}\sum_{l\in L} X_{ilt} = 1\ \ \forall i \tag{3}$$

$$\sum_{i\in I} X_{ilt} \le C_l^{\max}\ \ \forall l,t \tag{4}$$

Without loss of generality, it is assumed that no more orders are considered for assignment than total cycles are available throughout all periods and plants.

To anticipate the second assignment step and allow for its feasibility given the decisions of the first assignment step, both CS and LS constraints, found in (5) and (6) respectively, are considered on an aggregate basis as in Boysen et al. [5].

$$\sum_{i\in I} X_{ilt} \times B_{io} \le L_o^{CS} \times \frac{H_o}{N_o} \times C_l^{\max}\ \ \forall l,t,o \tag{5}$$

$$\sum_{l\in L}\sum_{i\in I} X_{il(t+Time_{ol}^{\text{Sup}})} \times B_{io} \le \frac{1}{K_t}\times\sum_{t'\in T}\sum_{l\in L}\sum_{i\in I} X_{il(t'+Time_{ol}^{\text{Sup}})} \times B_{io} \quad \forall t,o \tag{6}$$

$$\text{where } K_t = \frac{\sum_{t'\in T}\left(\min\left\{\max_l\left\{Time_{ol}^{\text{Sup}}\right\}, T-t'\right\}+1\right)}{L_o^{LS}\times\min\left\{\max_l\left\{Time_{ol}^{\text{Sup}}\right\}, T-t\right\}+1}$$

The existence of a maximum of options corresponding to each CS rule multiplied by the overall capacity can be seen as a necessary condition for achieving a feasible sequence. To increase the chance of obtaining such, the factors L_o^{CS} can be adjusted in the range $0 < L_o^{CS} \le 1$. [14]

The reasoning of Boysen et al. [13] is followed by using LS not as anticipation of sequencing, but for balancing material supply between periods. Materials are substituted by option choices and no differentiation between materials required for one option or interrelated material demands of options are considered. The factor L_o^{LS} with $1 \le L_o^{LS}$ further allows relaxation of the assumption of a uniform distribution of input [14].

Considering that final assembly on MMALs is close to the end of most value streams, reduction of bullwhip effects is more substantial if material is balanced higher upstream. Consequently, suppliers are focused rather than producers in the anticipation of material requirements and a derivate form of the LS-anticipation provided by Boysen et al. [5] is used. The parameter t thus describes the reference period for suppliers in inequality (6), while in (5) it shows the reference period for the plants. In (6) it is assumed that balancing the total amount of supply for any option throughout the planning horizon is sufficient to balance each supplier's workload. This is the case, for example, whenever option-related supplies for all plants are supplied by the same suppliers each. On the other extreme, whenever each plant uses its own suppliers, constraints can be considered on a per plant basis to achieve balancing of material supply. Furthermore, past and future orders are not considered $\left(X_{ilt'} = 0 \;\; \forall t' \notin T\right)$ and an approximately uniform distribution of supply lead times is presumed. Consequently, e.g., in period 1, material needs of orders are considered where the option supply time is at most T, while in period 3, only orders with supply times $\le T-3$ are regarded. The right side of the inequality is adjusted accordingly by the factor K_t that can easily be reconfigured in case other assumptions are made.

Altogether, both objectives of sequencing are taken into account – while CS focuses on throughput, LS focuses on input and both should be considered in global order assignment to allow for reasonable decision-making.

Bernoulli-distributed random variables can be found in (2), (5), and (6). Due to the planning horizon being medium in length, it seems reasonable to use the expected value $E[B_{io}]$ as an approximation within the objective function (3). While actual costs are then bound to deviate from the expected costs, deviations are unlikely to have much impact as long as cost objectives can be achieved on the long term by averaging the costs per period.

Within the constraints in (5) and (6), substitution of B_{io} by its expected value may improve solution accuracy whenever order assignments have to take place before specification. There is no guarantee, however, that feasibility can still be achieved. Due to the potential of prohibitively high cost of a global reallocation later on, e.g., because of already realized component ordering, infeasibilities are often unacceptable. To consider the potential of infeasibility, the model can be reformulated into a chance-constrained model:

$$P\left(\sum_{i\in I} X_{ilt}\times B_{io} \le L_o^{CS}\times\frac{H_o}{N_o}\times C_l^{\max}\right)\ge \alpha_{lto} \quad \forall l,t,o \tag{5.1}$$

$$P\left(\left(K_t-1\right)\sum_{l\in L}\sum_{i\in I} X_{il(t+Time_{ol}^{\text{Sup}})}\times B_{io} - \sum_{t'\in T,t'\neq t}\sum_{l\in L}\sum_{i\in I} X_{il(t'+Time_{ol}^{\text{Sup}})}\times B_{io} \le 0\right)\ge \alpha_{to} \quad \forall t,o \tag{6.1}$$

Due to (1), (5.1) is the cumulative distribution function (cdf) of the Poisson binomial distribution, which is explained in more detail, e.g., in [29]. To calculate (6.1), it is necessary to compute the cdf of the multiple of one Poisson binomial distribution minus another Poisson binomial distribution. To facilitate calculation, a simple but often highly effective approximation can be achieved with the normal distribution [29]. The difference of two distributions in (6.1) further increases the computational effort required, which can be avoided by approximating them. Using a normal approximation for each Poisson binomial distribution, one in (5.1) and two in (6.1), as well as subtracting the approximations within (6.1), leads to the following approximated constraints:

$$\Phi\left(\frac{L_o^{CS}\times\frac{H_o}{N_o}\times C_l^{\max}+0.5-\sum_{i\in I}X_{ilt}\times p_{io}}{\sqrt{\sum_{i\in I}X_{ilt}\times p_{io}\times(1-p_{io})}}\right)\ge\alpha_{lto} \quad \forall l,t,o \tag{5.2}$$

$$\Phi\left(\frac{0-EV_{to}}{\sqrt{Var}_{to}}\right)\ge\alpha_{to} \quad \forall t,o \tag{6.2}$$

$$\text{where } EV_{to} = \left(K_t-1\right)\left(\sum_{l\in L}\sum_{i\in I} X_{il(t+Time_{ol}^{\text{Sup}})}\times p_{io}-0.5\right) - \left(\sum_{t'\in T,t'\neq t}\sum_{l\in L}\sum_{i\in I} X_{il(t'+Time_{ol}^{\text{Sup}})}\times p_{io}-0.5\right)$$

$$\text{and } Var_{to} = \left(K_t-1\right)^2\left(\sum_{l\in L}\sum_{i\in I} X_{il(t+Time_{ol}^{\text{Sup}})}\times p_{io}\times\left(1-p_{io}\right)\right) + \sum_{t'\in T,t'\neq t}\sum_{l\in L}\sum_{i\in I} X_{il(t'+Time_{ol}^{\text{Sup}})}\times p_{io}\times\left(1-p_{io}\right)$$

4. Model application

With standard optimization tools like IBM ILOG CPLEX, the model is solvable to optimality in the deterministic case. The use of the chance-constrained model increases complexity of solving, however. Thus, a scenario-based approach should also be considered. This has the additional advantage that an assumption of independency is not required.

The approach is currently being validated in the case of an aircraft manufacturer, comparing both the chance-constrained model and a scenario-based approach.

A more general industrial applicability is also given for other companies operating global production networks with MMALs and planning unspecified customer orders in a mid-term horizon. An important assumption is that customer choices can be anticipated based on order history, which is likely to be the case in other capital goods industries, too. Depending on the options included in the model, option choices may be regarded as independent as introduced here. Furthermore, it is assumed that LS and CS are used for sequencing in a later planning step, which covers a wide range of industrial applications. If, however, different sequencing techniques are used, the anticipatory constraints need to be adjusted.

5. Summary and outlook

In this paper, an approach for the assignment of orders to plants and periods within global production networks was discussed in which final assembly of orders is completed at a range of plants with mixed-model assembly lines. Even though this planning process is highly relevant in practice, it was shown that such a procedure is discussed only to a slight degree in literature. Furthermore, order specification by customers is often considered in an ‘all or nothing’ approach; orders are either fully specified or assumed to be specified in mid-term production planning, or they are not considered individually at all. However, companies are likely able to attribute probabilities to option choices of individual customer orders.

A model was presented for mid-tem assignment of customer-specific orders to plants and periods in global production networks that considers the feasibility of the operational sequencing problem that is likely to take place at a later point in time, while also considering the uncertainty in order specifications.

Next, it will be necessary to complete validation of the approach with data from an industrial case.

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