Association for Information Systems
AIS Electronic Library (AISeL)

Wirtschaftsinformatik Proceedings 2007 | Wirtschaftsinformatik

February 2007

Order-driven planning in build-to-order scenarios

Thomas Volling
Technical University Braunschweig, t.volling@tu-braunschweig.de

Thomas Spengler
Technical University Braunschweig, t.spengler@tu-braunschweig.de

In: Oberweis, Andreas, u.a. (Hg.) 2007. *eOrganisation: Service-, Prozess-, Market-Engineering*; 8. Internationale Tagung Wirtschaftsinformatik 2007. Karlsruhe: Universitätsverlag Karlsruhe

ISBN: 978-3-86644-094-4 (Band 1)
ISBN: 978-3-86644-095-1 (Band 2)
ISBN: 978-3-86644-093-7 (set)

Order-driven planning in build-to-order scenarios

Thomas Volling, Thomas Spengler

Department of Production and Logistics Management
Technical University Braunschweig
38106 Braunschweig
{t.volling, t.spengler}@tu-braunschweig.de

Abstract

The adoption of build-to-order order fulfillment processes gives rise to a paradigm shift in production planning. Since all business is linked to customer orders, it is the order-driven planning activities that determine the success of operations. Therefore, a clear understanding of the associated planning tasks order promising and master production scheduling as well as their dynamic interaction is essential. Based on an analysis of the decision situation we provide a hierarchical framework comprising quantitative models for order promising and master production scheduling. The approach is evaluated using simulative analysis.

1 Introduction

The implementation of customer-oriented manufacturing strategies has frequently been associated with significant gains in profit and a competitive edge [GuNg05; ShLa05]. Yet, striving to serve high volume markets with individualized or customized products, new manufacturing concepts are needed. By switching to build-to-order (BTO) order fulfillment processes, companies seek to likewise benefit from characteristics like scale effects, standardized processes, and a high quality attributed to high volume make-to-stock strategies as well as from the high flexibility to adopt to diverse and changing market demand of make-to-order strategies [Pine99]. In doing so, mixed model assembly systems are the dominating production typology [BoFS06]. The constituting characteristic of this type is the coupling of assembly stations to flow-lines in a serial manner in accordance with the product structure. Mixed model assembly is thereby distinct from specialized flow-lines by the fact that a number of variants, or models respectively, is manufactured on the same production line. Facing heterogeneous production sequences, however, technological and organizational set-up efforts between consecutive models need to be reduced drastically. As a consequence, orders can be produced in lot sizes of one piece without loss of profitability [Scho99, 7].[1] Yet, considering the varying work content of different models at certain assembly stations, not every sequence is feasible given a line set-up. This problem of determining feasible production sequences is referred to as model-mix planning [WeKi64]. Sequence planning has attracted a lot of attention within the operations management community. The major implication of BTO, however, lies in the reduction of decoupling mechanisms against demand characteristics [GuNg05]. Production activities are thus subject to the induced variability and dynamics of the market. To be specific, these are characterized by the timing and characteristics of customer requests (i.e. the demand sequence), the resulting model-mix (demand structure), and the aggregated demand per period (demand level). At the same time, real-world production systems are characterized by a limited flexibility in terms of production and procurement capabilities. The synchronization of capacity with the volatility of the environment is therefore not viable. Instead, adequate control concepts are needed to match the supply of resources with the demand for products. These encompass policies for the determination of due dates in response to customer requests as well as for the consolidation of those promised orders into production plans. The associated planning tasks are referred to as order based planning.

Commercial applications to support order based planning have been introduced by leading business software providers as integral part of advanced planning and scheduling systems (APS).[2] Yet, to our knowledge, there is no analysis available boldfacing the performance of such systems in dynamic environments such as BTO scenarios. The answer to this question is in particular important, since the decision situation in real-world settings can be described by the complex interaction of planning functions, a high number of potentially influential parameters as well as an unknown dynamic performance of the decision support systems.

Against this background, the aim of this paper is to provide a hierarchical framework for order based planning in BTO scenarios, to develop mathematical programs for that framework and to evaluate the approach using simulation. The remainder is organized as follows: In section 2 we will highlight the decision situation of order based planning in BTO scenarios and review prior work on the subject. Based on that, models will be presented in section 3 and analyzed using simulation in section 4. Some concluding remarks are given in section 5.

---

[1] To be more specific, mixed-model flow lines typically require for an - on average - levelled load of their constituting stations. This prohibits extended sequences with similar capacity demand and therefore batch production.

[2] e.g. Real Time Positioning [SAP05], Global Order Promising [Orac05]

2 Decision Situation

Order based planning is distinct to its anticipative or push-based counterpart as to its reactive character (i.e. it regards orders placed instead of forecasted demand). The decision situation can thus be characterized as follows: In order to cope with the restricted capabilities to adjust capacities, the mid-term coordination on the basis of forecasts and orders at hand is essential. This results in aggregated production plans, which serve as cornerstones to synchronise further business functions like purchasing and capacity planning. The realisation of market demand in terms of customer orders requires for an adequate reaction. This function is usually denominated as *order promising* (OP) and comprises decisions about whether to accept or deny an order and which due date to promise [FlMe04]. Discrepancies between forecasting and orders placed as well as the potentially limited level of detail of OP might require for further adjustments to the plan. More specifically, promised due dates, instructions from the subordinate planning, characteristics of the production systems, and the ability to service new requests are to be taken into account. The resulting goal conflicts are to be resolved in the course of a second planning function called *master production scheduling* (MPS).

The complexity of the decision situation requires for an adequate structuring approach. In the following we will therefore present a hierarchical framework for order based planning in BTO scenarios. This lays the basis to reflect prior work in section 2.2 and to develop and evaluate decision models in sections 3 and 4.

2.1 Conceptual framework

Architectures of hierarchical planning systems are subject of numerous studies (e.g. [FlMe03; VBWJ05, 8]). However, these general frameworks need to be adopted in order to adequately fit decision models. Figure 1 depicts a framework for order-based planning in BTO scenarios and its interfaces to further planning tasks. The integral components are modules for OP and MPS.

Considering OP, requirements in terms of customer response time, the reliability and level of detail of the quoted offer as well as restrictions regarding the availability of resources have to be taken into account. Also, OP procedures usually have to cope with a high number of requests, which induce significant dynamics into planning. Finally, instructions from the subordinate demand planning (e.g. quotas regarding volumes dedicated to certain distribution channels) might need to be incorporated. The outcome is a pool of fully specified orders (in terms of product configuration and delivery date) which is transferred to MPS. More specifically, MPS seeks to coordinate production, procurement, and sales on the short-run in order to facilitate efficient resource utilization [VBWJ05, 169; FlMe04]. Considering production and procurement, a leveled demand, i.e. a stable utilization of the resources (including demand for components) is to be achieved [EnZi98]. A specific objective could be to minimize deviations from specific levels of capacity utilization, which determine efficient operating points of the production line [Bola03]. The same holds true for component demand. Usually minimal and maximal levels are agreed on by means of mid-term supply contracts. With respect to sales, the ability to service newly arriving orders is of great importance. That means that MPS ought to minimize bottlenecks. Planning objects are specified orders, which are to be assigned to production lines and periods. Capacities are usually treated as fixed, as provided by the master production planning [Scho99, 111]. Executing MPS results in aggregated plans that are passed on to sequencing and material requirements planning for further detailing.

With an increasing number of orders becoming known as time progresses, the question of identifying adequate re-planning frequencies arises. A high frequency results in a high number of changes to the plan, which contradicts the aim of a stable coordination. A low frequency, on the contrary, potentially results in a delayed transfer of planning information. The integrated assessment of OP and MPS therefore seems to be inappropriate.

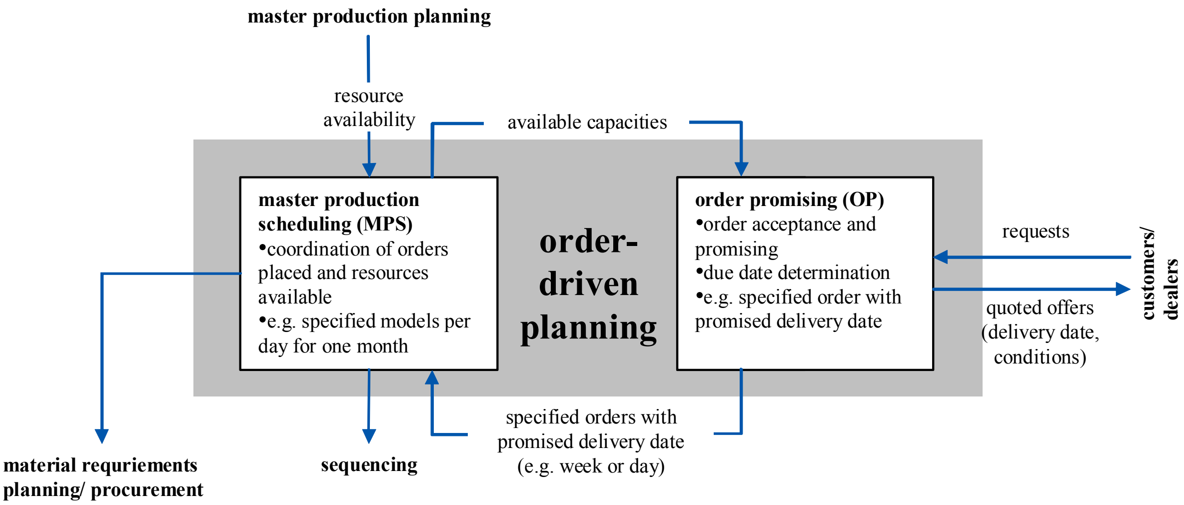

Figure 1: Framework for order based planning in BTO scenarios

Reconsidering the proposed framework, the decision situation can be interpreted as a hierarchical system composed of OP and MPS [SpVR06]. Referring to the work from [Schn03] this setting is called tactical-operational. More specifically, OP determines due dates for newly arriving orders (the so called factual instruction) considering the information available at the times of its execution (e.g. at each order arrival). In a second frequency, but usually at a later point in time, MPS is executed, given the prior instructions, i.e. all promised orders up to that point in time, with the aim to assign these to planning periods (the final instruction). The decision of MPS is thereby dependent on that of OP, such that it constitutes the operational level within the horizontal hierarchy while OP demarks the tactical level. The final instruction, i.e. the aggregated production plan, depends on both decisions.

2.2 Related work

Approaches to order based planning in BTO scenarios are subject of two streams of research. These have on the one hand evolved from work on mixed-model assembly line balancing and sequencing and were on the other developed under the denomination available-to-promise (ATP) as part of work on hierarchical production planning and control systems (e.g. APS).

Regarding the former, aspects of order based planning have been incorporated into sequencing, i.e. the determination of optimal production sequences by means of model-mix planning. These approaches are, however, based on the assumption, that orders are exogenously given [Scho99, 107]. With respect to the framework introduced above, this means, that only the MPS-functionality is being investigated. Also, considering planning horizons needed for the reasonable leveling of production, the computational burden to solve the detailed sequencing problems is prohibitive.[3] Therefore aggregated models have been presented in recent contributions.

[Bola03] provides solution procedures for the problem to select orders to be produced in the upcoming period out of a pool of promised orders. The objective is to minimize delivery date dependent costs. Leveling aspects are incorporated in setting ranges for acceptable capacity utilization levels. Potential gains of a branch & bound procedure to solve the resulting multi-dimensional knapsack problem are illustrated by a numerical analysis. In a recent publication [Boys05] presents a model that explicitly incorporates desired due dates into MPS for mixed-model assembly. The objective is to minimize delivery dependent costs. Also extensions to line assignment and leveling are provided. Both approaches do not distinguish between OP and MPS. The requirements of order based planning are therefore only partly satisfied.

ATP approaches, on the contrary, focus on decision support for OP. In analogy to the approaches discussed before, *optimization based batch ATP* aims at processing a pool of specified but not yet promised orders at hand (i.e. either rejecting or quoting each order). The objective is to maximize profit. Results include promised due dates and delivery conditions. Optimizing

[3] Even the sequencing problem for single stations is NP-hard [Tsai95].

batch models have been discussed by [ChZB02] as well as [Pibe05]. These models seek to maximize contribution margin with respect to real (e.g. holding, production, and procurement costs) and 'soft costs' (e.g. costs for late delivery or for low capacity utilization). A central premise of those approaches is, that in the course of sequential approach, promised due dates and quantities are treated as fixed restrictions for subsequent planning cycles. Accordingly, good results have been numerically proven for rather large batching intervals. A reduction of the intervals, however, results in the significant deterioration of the planning performance. A similar model structure is introduced by [FlMe04]. To avoid the illustrated drawbacks of short batching intervals, the authors propose the coupling with MPS. They however do not elaborate on the consequences in terms of modeling and performance. *Rule based batch ATP* aims at defining decision rules for the acceptance of orders [KiSc05]. A hierarchical approach is provided by [JSJK02] for the case of LCD production. The authors differentiate between a rule-based OP routine and a heuristic to determine the unused capacity based on a detailed schedule in a job-shop setting. The approach, however, does not incorporate the specific characteristics of BTO as described above. This in particular holds true for the requirements of high variance flow-shop production. A drawback of batch approaches is that they do not support the interaction between customer and company. *Rule-based real-time approaches* in contrast build on an ad-hoc assessment of the ability to deliver at a certain point in time. A recent review is given by [MGGP04]. Various extensions incorporating sophisticated statistics as well as stochastic influences have been published (e.g. [WGHH04]). The aggregated assessment seems adequate for decoupled production systems. It in turn does not reflect aspects like leveling, which are special to BTO settings. *Optimization based real-time approaches* have to our knowledge only been presented for academic examples (e.g. [Kate94]). The objective is to quickly determine detailed schedules. Due to the complexity of the problem the scalability of the approach is limited.
To sum up, knowledge on the performance of planning schemes, in particular regarding the interplay of OP and MPS, is limited. In the following we will therefore provide a mathematical program for order based planning in BTO scenarios.

3 Modeling

An adequate model to support order based planning in BTO scenarios has to cope with the divergent requirements of the customer interaction on the one hand and resource related aspects on the other. We therefore chose a hierarchical approach, comprising a real-time ATP model as well as a MPS model for mixed-model assembly planning on rolling horizons.

3.1 The order acceptance problem

Time is discretized in equidistance planning periods $t=1,2,\ldots,T^{max}$. Orders i ($i=1,\ldots,I$) arrive randomly and are evaluated individually upon their arrival. Evaluation thereby refers to the determination of a production period τ ($\tau = t,\ldots,T^{max}$), considering capacities available and starting from the first disposable period t. Production coefficients a_{ir} are used to transform each order's specific product configuration into capacity requirements for each resource r. They likewise reflect the demand for resource capacity of the production system ($r\in\Omega^1$) as well as those of component availability usually referred to as ATP ($r\in\Omega^2$). The cumulated index set of all resources will be referred to as Ω ($\Omega = \Omega^1 \cup \Omega^2$). We assume that all orders have been economically evaluated by means of a subordinate demand management and have positive contribution margins. Orders have been back scheduled with respect to their production and distribution lead times, such that the analyses can be restricted to the (planned) start of production. Alternative production facilities are not considered.

A bucketized model for the binary assignment of order i to planning period τ is therefore given by (1)-(4). In the course of OP, each order is being assigned to a period within the planning horizon $[t, T^{max}]$, such that the associated costs are minimized (1). Due to the real-time execution mode, each order is treated separately. This decision is modeled by the vector $\mathbf{x}_i$ with the elements $x_{i\tau}$, which are set to 1 if the order is assigned to the particular period and 0 if otherwise. The relevant costs of an assignment $c_{i\tau}$ reflect the customer preferences and are a function of the requested period and the promised period.[4] Inequalities (2) incorporate resource constraints into the model. $ctp_{r\tau}$ thereby refers to the available capacity at the time of the order arrival and is updated with each order being processed. Equations (3) assure that the order is assigned to a period. The result of the OP procedure is a promised planning period, or the corresponding delivery date respectively, for a certain product configuration.

$$\textit{Minimize} \qquad C^{OP}(\mathbf{x}_i) = \sum_{\tau=t}^{T^{\max}} c_{i\tau} \cdot x_{i\tau} \tag{1}$$

$$x_{i\tau} \cdot a_{ir} \le ctp_{r\tau} \quad \forall r \in \Omega, \tau = t,\ldots,T^{\max} \tag{2}$$

[4] For an in-depth discussion of time dependent costs refer to [Bola03].

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

$$x_{i\tau} \in \{0,1\} \;\; \forall\, \tau = t,\ldots,T^{\max} \quad (4)$$

3.2 The master production scheduling problem

The decision to come to in the course of the MPS procedure is to determine final planning periods for the set of promised but not finalized orders Ψ. The MPS is executed on rolling horizons once every planning period with a planning horizon of T periods. Accordingly only the first planning period is put into practice, while the others are being updated with respect to the new information available (i.e. the newly promised orders). Since both, restrictions of the production system as well as those regarding component availability have to be incorporated into the decision making to assure feasibility, we use a differentiated definition of capacity: considering a flow-shop, the maximum capacity per period $\mathrm{cap}_\tau^{\max}$ is given by the quotient of the overall production time Q_τ and the cycle time W_τ. In addition to that, model-mix restrictions have to be incorporated into the calculus to adequately reflect the sequencing limitations of the prevailing mixed-model production system. Therefore we reduce the overall capacity of the production system by means of a coefficient α_r for each capacitated resource $r \in \Omega^1$.[5] The maximum aggregated capacity available per resource and period is hence given by $\alpha_r \cdot \mathrm{cap}_\tau^{\max}$. Further resource restrictions ($r \in \Omega^2$) regard maximum levels for the component availability in a planning period $\mathrm{cap}_{r\tau}^{SM}$. These do not depend on the subsequent sequencing and can consequently be assumed exogenously given (e.g. by the subordinate planning). Accordingly, the maximum capacity of resource r in period τ is given by:

$$\mathrm{cap}_{r\tau}^{\max} = \begin{cases} \alpha_r \cdot \mathrm{cap}_\tau^{\max} & \text{if } r \in \Omega^1, \\ \mathrm{cap}_{r\tau}^{SM} & \text{if } r \in \Omega^2. \end{cases} \quad (5)$$

In order to reflect the divergent requirements discussed above we implemented two intervals for the objective function: the first interval ranges from t to k and the second one from k+1 to the end of the planning horizon, with $t \le k \le t + T - 1$. Let further $\mathrm{ctp}_{r\tau}^{-}$ denote the standardized

[5] To determine α_r so called $H_o{:}N_o$ - rules have been used. The interpretation is, that no more than H_o units out of a sequence with length N_o may require an option o or a corresponding resource r respectively [DrKi01].

deviations to the target capacity consumption level $cap_{r\tau}^{min}$ and $ctp_{r\tau}^{+}$ the capacity available $ctp_{r\tau}$ standardized with respect to the maximum capacity level $cap_{r\tau}^{max}$. We furthermore used the weighting functions $P_{r\tau}^{leveling}(\cdot)$ to assess deviations to the targeted capacity utilization of resource r in period τ (leveling aspects) and $P_{r\tau}^{service}(\cdot)$ to assess the available capacity of resource r in period τ (measure of the ability to service new orders). Finally, $\bar{c}_{i\tau}$ denotes the cost of assigning order i to period τ.[6] The program MPS is thus given as:

$$Minimize\ \ C^{MPS}(\bar{\mathbf{x}}) = \sum_{\tau=t}^{t+k} \sum_{r\in\Omega} P_{r\tau}^{leveling}\left(ctp_{r\tau}^{-}\right) - \sum_{\tau=t+k+1}^{t+T-1} \sum_{r\in\Omega} P_{r\tau}^{service}\left(ctp_{r\tau}^{+}\right) + \sum_{\tau=t}^{t+T-1} \sum_{i\in\Psi} \bar{c}_{i\tau} \cdot \bar{x}_{i\tau} \quad (6)$$

w.r.t.

$$\frac{cap_{r\tau}^{min} + ctp_{r\tau} - cap_{r\tau}^{max}}{cap_{r\tau}^{min}} \le ctp_{r\tau}^{-} \quad \forall r \in \Omega; \tau = t,...,t+k \quad (7)$$

$$\frac{ctp_{r\tau}}{cap_{r\tau}^{max}} \ge ctp_{r\tau}^{+} \quad \forall r \in \Omega; \tau = t+k+1,...,t+T-1 \quad (8)$$

$$\sum_{i\in\Psi} \bar{x}_{i\tau} \cdot a_{ir} = cap_{r\tau}^{max} - ctp_{r\tau} \quad \forall r \in \Omega; \tau = t,...,t+T-1 \quad (9)$$

$$\sum_{\tau=t}^{t+T-1} \bar{x}_{i\tau} = 1 \quad \forall i \in \Psi \quad (10)$$

$$ctp_{r\tau}, ctp_{r\tau}^{-}, ctp_{r\tau}^{+} \ge 0 \quad \forall \tau = t,...,t+T-1 \quad (11)$$

$$\bar{x}_{i\tau} \in \{0,1\} \quad \forall i \in \Psi, \tau = t,...,t+T-1 \quad (12)$$

The assignment is modeled by matrix $\bar{\mathbf{x}}$ with T-dimensional column vectors $\bar{\mathbf{x}}_i$. Doing so, the binary vector elements $\bar{x}_{i\tau}$ are set to 1 if an order i is assigned to period τ in analogy to the OP procedure described above. The objective of the MIP (6)-(12) is then to minimize the relative deviations to the targeted utilization levels $ctp_{r\tau}^{-}$ weighted by $P_{r\tau}^{leveling}(\cdot)$ throughout the interval [t, t+k] and to maximize the weighted capacity available $ctp_{r\tau}^{+}$ as given by $P_{r\tau}^{service}(\cdot)$ throughout the interval [t+k+1, t+T-1]. In addition to that, service objectives are to be incorporated by means of the cost of assigning order i to period τ. The figures for the first interval result from standardizing shortfalls on the targeted capacity utilization $cap_{r\tau}^{min}$ according to inequali-

[6] These are in contrast to $c_{i\tau}$ a measure of bringing forward or delaying an order given a specified promised delivery date and therefore reflect e.g. holding costs or penalties respectively.

ties (7) (figure 2). Those of the second interval are calculated as given by inequalities (8). Constraints (9) assure feasibility with respect to resource capacities, whereas $ctp_{r\tau}$ specifies the prevailing slack. Set coverage constraints (10) assure that each order is assigned to one period while constraints (11)-(12) define non-negativity and binary coding for the variables. The two models are coordinated by means of the coupling conditions (9) (bottom-up) and the service costs $\bar{c}_{i\tau}$ (top-down), since they depend on the promised period.

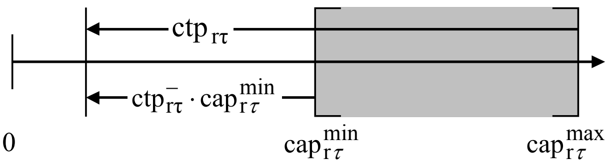

Figure 2. Determination of the standardized deviation to the targeted minimal capacity utilization

To demonstrate the meaning of the segmented objective function, refer to the illustrative example depicted in figure 3. The figure shows the distribution function and the expected number of customer orders placed y as a function of the period x within the planning horizon, given a demand of 20 orders per planning period and normal distributed ordering lead times with a mean of 10 and a standard deviation of 3 periods (i.e. considering the 10^{th} period of the planning horizon, on average 50% of all customers demanding a product for that particular period will have placed their orders at the time of the MPS execution). Given a targeted level for the minimal capacity utilization of 80% (i.e. 16 orders per period) two intervals can be identified. For period 1 to 7, the expected orders transcend the critical level, while the opposite is true for periods 8 to 21. By segmenting the objective function, a stable resource utilization can be pursuit in the first interval for which (on average) most orders have been placed, while at the same time bottlenecks can be avoided in the second one with a high (expected) inflow of new orders.

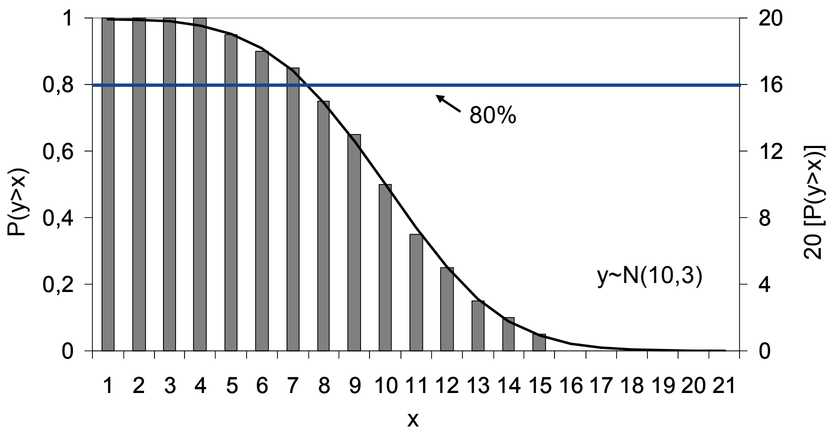

Figure 3: Illustrative order arrival pattern for $y \sim N(10;3)$

The implementation of the objective function requires to economically assess the particular terms. Monetary consequences of an unbalanced model-mix include costs for extra staff, overtime, or a reduced productivity (e.g. due to slack) as well as additional procurement costs. Monetary consequences of a reduced responsiveness include lost revenues (i.e. opportunity costs) since newly arriving orders cannot be served (lost sales). The explicit determination of monetary consequences often raises difficulties in real-world settings, since data is not available in the sufficient quality or the computational complexity does not allow for an explicit determination. This essentially leads to a multi-criteria decision situation. For such settings, additive weighting functions have been used to identify compromise solutions [RoWa05].

The models introduced above are characterized by a high number of parameters influencing the static but in particular the dynamic performance, i.e the interplay of OP and MPS. For similar settings, simulation studies have been used successfully. In the remainder, we will evaluate the presented framework using discrete-event simulation.

4 Simulation experiments

The scope of the following evaluation is twofold: at first it is to be shown, that the structure of the MPS objective function controls the simulation response and, in doing so, to numerically proof the meaning of the two objective function intervals. A second objective is to analyze the performance of the presented approach. Therefore we will compare the performance of the proposed framework to a policy restricted to OP (i.e. no MPS execution). The analysis is performed in three steps. At first, a demand sequence is generated for each replication. More specifically, each sequence comprises a set of orders with a specific configuration, an order date, and a preferred delivery date. In a second step, this demand sequence is subject to the order based planning approach to be analyzed. Accordingly, each order is at first promised individually and secondly assigned to a production period in the course of a MPS procedure executed on rolling horizons. In a third step, the results are evaluated. For the implementation we used eM-Plant as simulation tool and the commercial solver Lingo to solve the mathematical programs.

4.1 Experimental Data and Performance Measures

We considered an autoregressive moving-average demand process to derive the aggregated demand level d_τ of period τ according to $d_\tau = 20 + 0.8 \cdot (d_{\tau-1} - 20) - 0.1 \cdot \varepsilon_{\tau-1} + \varepsilon_\tau$ with

$\varepsilon_i \sim N(0;2)$. In a second step, we calculated normal distributed lead times with a mean of 10 and a standard deviation of 3 periods and subtracted them from the designated production period to achieve individual order arrival times.[7] These arrival times were then used to synthesize the consolidated demand stream. Finally, capacity coefficients a_{ir} were derived according to take-rates $take_r$ for each of the two resource r using a uniformly (0,1)-distributed random number rnd as suggested by [Boys05]:

$$a_{ir} = \begin{cases} 1 & \text{if } rnd \le take_r, \\ 0 & \text{else.} \end{cases} \tag{13}$$

For the analysis we assumed $\text{take}_1 = 0.7$ and $\text{take}_2 = 0.3$. Each simulation run covered 40 periods such that on average 800 orders were processed. MPS was executed once every period. In order to evaluate the effect of the capacity/demand ratio λ, we set the maximum capacity per resource and period to $\text{cap}_{r\tau}^{\max} = \lambda \cdot \text{take}_r \cdot E[d_\tau]$. The minimal targeted capacity utilization $\text{cap}_{r\tau}^{\min}$ was set to 80% of the maximal capacity. We assumed a linear cost function to determine $c_{i\tau}$: each period earlier than the requested added 1 unit to the costs while each period later than the requested added 5 units. $\bar{c}_{i\tau}$ was assumed to be the same as $c_{i\tau}$ for earliness; lateness was not allowed for. Accordingly, the following term was added to the MPS model.

$$\sum_{\tau=t}^{t+T-1} \tau \cdot (\bar{x}_{i\tau} - x_{i\tau}) \le 0 \quad \forall i \in \Psi \tag{14}$$

(Piecewise) linear terms were implemented to evaluate the effect of the first two terms of the MPS objective function using the coefficients p_1 and p_2 ((15) and (16)). The interval parameter k was set to 6.

$$P_{r\tau}^{\text{leveling}}(\text{value}) = p_1 \cdot \text{value} \tag{15}$$

$$P_{r\tau}^{\text{service}}(\text{value}) = \begin{cases} 0 & \text{for value} < 0.5 \cdot \text{cap}_{r\tau}^{\max}, \\ p_2 \cdot \text{value} & \text{for value} \ge 0.5 \cdot \text{cap}_{r\tau}^{\max}. \end{cases} \tag{16}$$

We incorporated four objectives into the analysis. At fist, the total under-utilization and the standard deviation of the utilization were evaluated as measures for the compliance with resource-oriented objectives. In addition to that, we analyzed the customer-oriented performance

[7] The reason for the differentiated approach is that the order behavior might be explained with the central limit theorem, since it reflects the behavior of a large number of independent entities (i.e. the customers). The demand level, however, underlies various influences which might cause auto correlation (e.g. hockey stick effect, marketing campaigns). Ongoing research seeks to build a more thorough understanding of the arrival process.

be means of the average costs of the assignment in the course of OP and the standard deviation of this figure. Figures were computed as given in the appendix.

4.2 Experimental Design

A full factorial design was used to evaluate the structure of the MPS objective function. The aim was to deduce the importance of the two objective function intervals in terms of their main effects and interactions. Since the performance of order based planning was expected to depend on the capacity/demand ratio, we added it as another experimental factor. Using two levels for each factor (i.e. 2^k-factor design) cumulated in 2^3=8 configurations (called scenarios in the following). 80 replications were run for each scenario. Since we expected all performance measures to strongly correlate with the demand scenario (i.e. number of orders, preferred lead time, and model-mix), we used a common random number approach. Table 1 summarizes the factors and levels used for the analysis.

factor	denomination	levels	degrees of freedom
weighting of the leveling term	p_1	10-10,000	1
weighting of the service term	p_2	10-10,000	1
capacity/demand ratio	lambda	1.0-1.2	1

Table 1: Factorial design

4.3 Numerical Results

The results of the analysis are shown in the subsequent profile plots (figure 4 and 5). Depicted are the estimated means for the particular scenarios as compared to the performance of the policy restricted to OP (baseline policy in the following).[8] The slope can be interpreted as the (main) effect of changing p_2 from its low level to its high level, while the offset is attributed to the level of p_1. A change in the offset indicates interaction effects between the factors. Hence, the findings can be summarized as follows. p_1 affects all performance measures positively. The effect is in particular relevant for the resource-oriented objectives and a high capacity/demand ratio. This finding seems intuitively clear, since the first interval explicitly seeks to minimize deviations to the minimal targeted capacity. p_2 positively affects both the customer and the resource-oriented performance measures for tight capacity scenarios while the opposite is true for the customer-oriented figures and a high capacity/demand ratio, yet on a very low (absolute)

[8] Doing so, we standardized the difference between each scenario's results and the baseline policy's with respect to the baseline policy. Accordingly, higher values indicate a better performance.

level. There is no effect of p_2 regarding the resource-oriented objectives for a high capacity/demand ratio. The analysis does not show any major interaction effects.

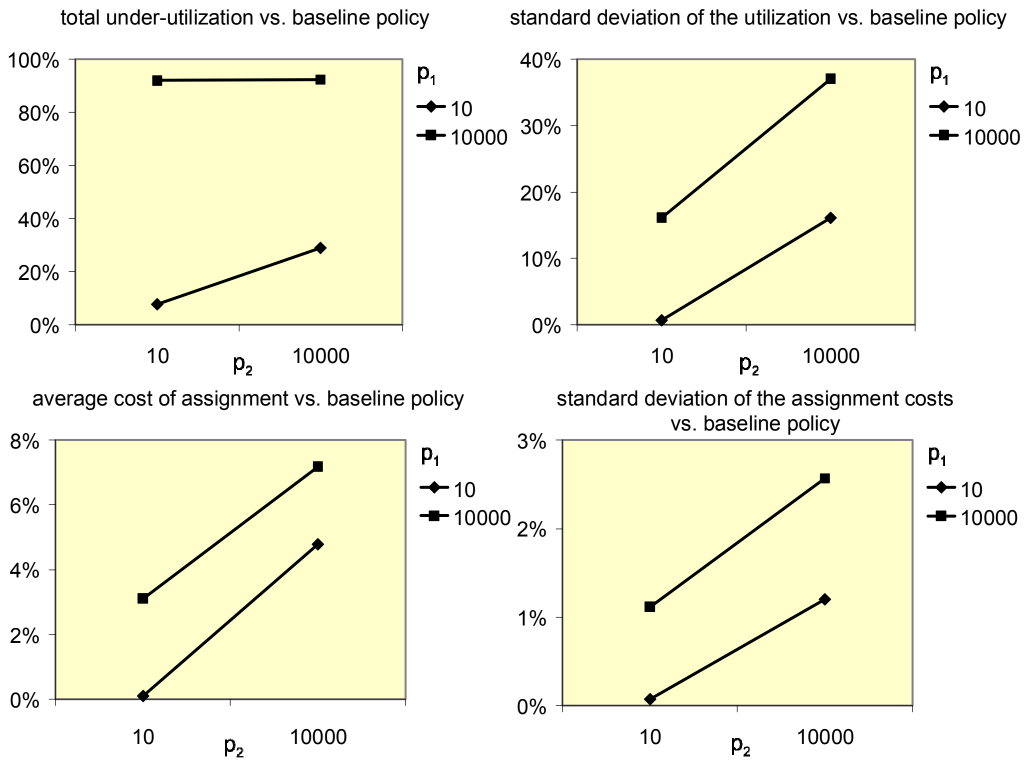

Figure 4: Profile plots for capacity/demand ratio 1.0 (all figures are standardized with respect to the baseline policy)

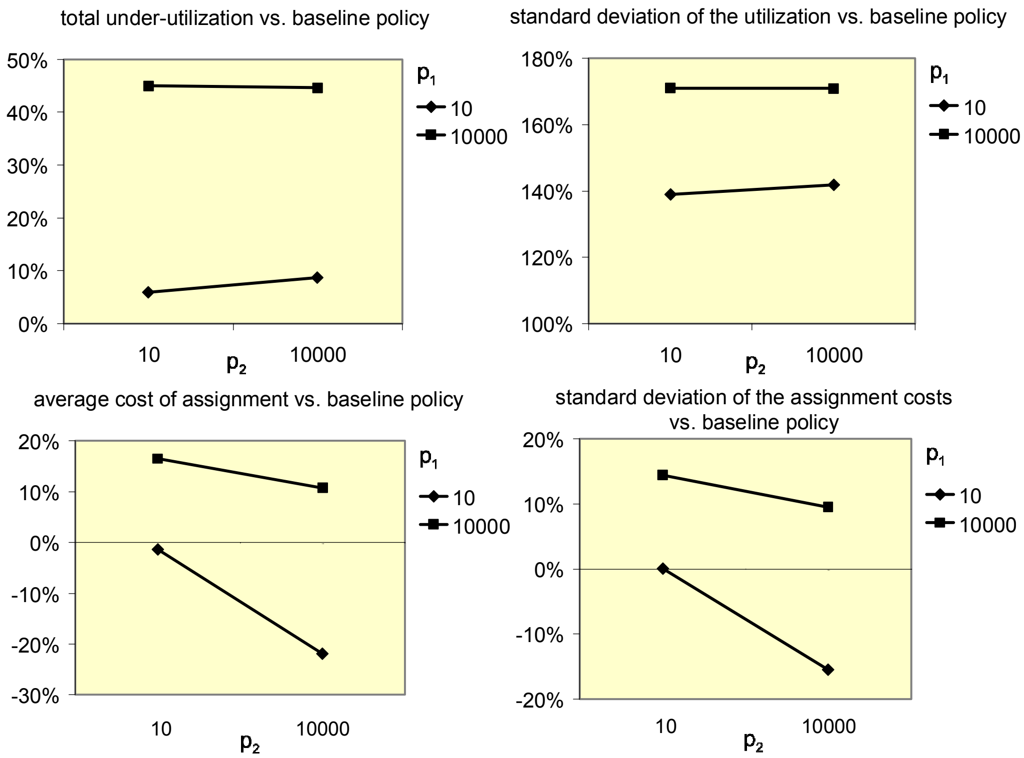

Figure 5: Profile plots for capacity/demand ratio 1.2 (all figures are standardized with respect to the baseline policy)

Overall, the average absolute levels of the customer-oriented objectives for the low capacity/demand ratio by far exceed those for the high capacity/demand ratio (18 times for the average costs and 6 times for the standard deviation) while the opposite is true for the resource-oriented ones (10 times for the under-utilization and 2 times for the standard deviation). This indicates an increased relevance of customer-oriented objectives if capacity is tight and of resource-oriented for excess capacity settings vice versa. Considering the factor combinations with p_1 and p_2 likewise being on their low and high levels respectively, discrepancies in the performance measures are caused by the relative importance as compared to the third term of the MPS objective function, i.e. the cost of the assignment.

5 Conclusions

Changing to BTO strategies, companies face an increased exposure to market dynamics. Since all business is linked to customer orders, it is the order-driven planning activities that determine the success of operations. Therefore, a clear understanding of the associated planning tasks OP and MPS as well as their dynamic interaction is essential. In this paper we provided an analysis of the decision situation of order based planning in BTO scenarios by means of a hierarchical framework, developed distinct models for OP and MPS and evaluated these using simulation.

Following the analysis, the presented approach seems promising to improve order based planning in BTO scenarios. The performance in both, customer and resource-oriented objectives is significantly controlled by the interplay of MPS and OP as well as the structure of the MPS objective function. As compared to a policy restricted to OP, improvements of 7% regarding the average cost of assignment and 45% regarding the total under-utilization can be achieved. Also, by decomposing OP and MPS, customers benefit from an instantaneous response to their requests and can thus evaluate different configurations with respect to their delivery date before placing their order. The production system on the contrary benefits from a stable coordination which is facilitated by MPS.

The scope of this study was on rather general insights into the dynamic behavior of order based planning. Consequently, the models are thought to be just as specific as to reflect the general characteristics of BTO scenarios. More work is needed to improve the empirical basis of the approach and to deepen the understanding of the dynamic performance as to provide guidance for the configuration of the presented models for specific settings.

Appendix

Table 2: Performance measures (Asteroids indicate the factual or final assignment (i.e. the promised period and the final date of production); T* denominates the simulation run length)

resource-oriented	total under-utilization	$\sum_{r\in\Omega}\sum_{\tau=1}^{T^*}\left(\max\left(\mathrm{cap}_{r\tau}^{\min}+\sum_{i\in\Psi}\overline{x}_{i\tau}^{*}\cdot a_{ir}-\mathrm{cap}_{r\tau}^{\max};0\right)\Big/\mathrm{cap}_{r\tau}^{\min}\right)$
	standard deviation of the utilization	$\sum_{r\in\Omega}\sqrt{\sum_{\tau=1}^{T^*}\left(\left(ctp_{r\tau}^{+}\right)^{*}-\left(ctp^{+}\right)^{*}\right)^{2}\Big/T^{*}-1}\Big/\lvert\Omega\rvert$, with $\left(\mathrm{ctp}_{r\tau}^{+}\right)^{*}=\left(\sum_{i\in\Psi}\overline{x}_{i\tau}^{*}\cdot a_{ir}\right)\Big/\mathrm{cap}_{r\tau}^{\max}\quad\forall r\in\Omega;\tau=1,\ldots,T^{*}$ $\left(\mathrm{ctp}^{+}\right)^{*}=\left(\sum_{\tau=1}^{T^*}\sum_{r\in\Omega}\left(\mathrm{ctp}_{r\tau}^{+}\right)^{*}\right)\Big/\lvert\Omega\rvert\cdot T^{*}$
customer-oriented	average cost of assignment	$\left(C^{OP}\right)^{*}=\sum_{i\in\Psi}\sum_{\tau=1}^{T^*}c_{i\tau}\cdot x_{i\tau}^{*}\Big/\lvert\Psi\rvert$
	standard deviation of the assignment costs	$\sqrt{\left(\left(\sum_{i\in\Psi}\sum_{\tau=1}^{T^*}c_{i\tau}\cdot x_{i\tau}^{*}\right)-\left(C^{OP}\right)^{*}\right)^{2}\Big/\lvert\Psi\rvert-1}$

References

[Bola03] *Bolat, Ahmet*: A mathematical model for selecting mixed models with due dates. In: International Journal of Production Research 41 (2003) 5, p. 897-918.

[BoFS06] *Boysen, Nils; Fliedner, Malte; Scholl, Armin*: A classification of assembly line balancing problems. Wirtschaftswissenschaftliche Fakultät, Jena 2006.

[Boys05] *Boysen, Nils*: Produktionsprogrammplanung bei Variantenfließfertigung. In: Zeitschrift für Planung und Unternehmenssteuerung 16 (2005) 1, p. 53-72.

[ChZB02] *Chen, Chien-Yu; Zhao, Zhenying; Ball, Michael O.*: A model for batch advanced available-to-promise. In: POM 11 (2002) 4, p. 424-440.

[DrKi01] *Drexl, Andreas; Kimms, Alf*: Sequencing JIT mixed-model assembly lines under station-load and part-usage constraints. In: Mgt. Sci. 47 (2001) 3, p. 480-491.

[EnZi98] *Engel, Christoph; Zimmermann, Jürgen*: Objectives for order-sequencing in automobile production. In: Drexl, A.; Kimms, A. (eds.): Beyond manufacturing resource planning, Springer, Berlin 1998, p. 307-331.

[FlMe03] *Fleischmann, Bernhard; Meyr, Herbert*: Planning hierarchy, modeling and advanced planning systems. In: de Kok, A.; Graves, S. (eds.): Supply chain management, Elsevier, Amsterdam 2003, p. 457-523.

[FlMe04] *Fleischmann, Bernhard; Meyr, Herbert*: Customer orientation in advanced planning systems. In: Dyckhoff, H.; Lackes, R.; Reese, J. (eds.): Supply chain management and reverse logistics, Springer, Berlin 2004, p. 297-321.

[GuNg05] *Gunasekaran, A.; Ngai, Eric W.T.*: Build-to-order supply chain management. In: Journal of Operations Management 23 (2005) 5, p. 423-451.

[JSJK02] *Jeong, Bongju; Sim, Seung-Bae; Jeong, Ho-Sang; Kim, Si-Won*: An available-to-promise system for TFT LCD manufacturing in supply chain. In: Computers Industrial Engineering 43 (2002) 1, p. 191-212.

[Kate94] *ten Kate, Hans A.*: Towards a better understanding of order acceptance. In: International Journal of Production Economics 37 (1994) 1, p. 139-152.

[KiSc05] *Kilger, Christoph; Schneeweiss, Lorenz*: Demand fulfilment and ATP. In: Stadler, H.; Kilger, C. (eds.): Supply chain management and advanced planning, Springer, Berlin 2005, p. 179-195.

[MGGP04] *Moses, S.; Grant, H.; Gruenwald, L.; Pulat, S.*: Real-time due-date promising by build-to-order environments. In: IRPR 42 (2004) 20, p. 4353-4376.

[Orac05] Oracle: Fact Sheet Global Order Promising 10i.10. Redwood Shores, CA, 2005

[Piber05] *Pibernik, Richard*: Advanced available-to-promise. In: International journal of production economics 93-94 (2005), p. 239-252.

[Pine99] *Pine, B. Joseph*: Mass customization: the new frontier in business competition. Harvard Business School Press, Boston, Mass. 1999.

[RoWa05] *Rohde, Jens; Wagner, Michael*: Master planning. In: Stadtler, H.; Kilger, C. (eds.): Supply chain management and advanced planning, Springer, Berlin 2005, p. 159-177.

[SAP05] *SAP*: "Managing the e-supply chain in der Automobilindustrie mit mySAP Automotive", Walldorf, 2005.

[Schn03] *Schneeweiß, Christoph A.*: Distributed decision making. Springer, Berlin 2003.

[Scho99] *Scholl, Armin*: Balancing and sequencing of assembly lines. Physica, Heidelberg 1999.

[ShLa05] *Sharma, Arun; Laplaca, Peter*: Marketing in the emerging era of build-to-order manufacturing. In: Industrial Marketing Management 34 (2005) 5, p. 476-486.

[SpVR06] *Spengler, Thomas; Volling, Thomas; Rehkopf, Stefan:* Taktisch-operative Planung bei variantenreicher Serienfertigung. In: Jacquemin, M.; Pibernik, R.; Sucky, E. (eds.): Quantitative Methoden der Logistik und des Supply Chain Management, Dr. Kovac, Hamburg 2006, p. 183-210.

[Tsai95] *Tsai, Li-Hui*: Mixed-model sequencing to minimize utility work and the risk of conveyor stoppage. In: Management Science 41 (1995) 3, p. 485-495.

[VBWJ05] *Vollmann, Thomas E.; Berry, William L.; Whybark, D. C.; Jacobs, F. Robert*: Manufacturing planning and control systems for supply chain management. McGraw-Hill, New York, NY 2005.

[WeKi64] *Wester, L.; Kilbridge, M.*: The assembly line mixed model sequencing problem. In: Proceedings of the 3rd International Conference on OR (1964) p. 247-260.

[WGHH04] *Wullink, G.; Gademann, A.J.R.M.; Hans, E.W.; van Harten, A.*: Scenario-based approach for flexible resource loading under uncertainty. In: International Journal of Production Research 42 (2004) 24, p. 5079-5098.