SIMULATION OF ROBUST MASTER PRODUCTION SCHEDULING IN AN INDUSTRIALLY RELEVANT PLANNING ENVIRONMENT

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KEYWORDS
Robust optimisation, production planning, simulation.

ABSTRACT

This paper presents a simulation analysis on the effects of robust master production scheduling. Up to now, relatively highly aggregated planning models for robust master production scheduling were regarded and the realizability of the planning results was not considered. This paper analyses a more detailed model for master production scheduling than in previous works. The evaluation of the planning results is made by providing the planning results to the subsequent planning levels in a hierarchical production planning system and realizing them in a realistic production system. The primary objective of the production system is to minimise tardiness of customer order deliveries. The secondary objective is to minimise inventory of end products. It is shown that robust master production scheduling in such a planning system leads to significant reductions of tardiness of customer order shipment. Compared to an equivalent deterministic approach for master production scheduling, the mean customer order backlog is reduced more than the mean inventory levels are increased.

INTRODUCTION

For a long time, concepts for hierarchical production planning – for example in (Hax and Meal 1975) – have been established in research and industry. In this paper, the planning concept proposed in (Drexl et al. 1994) and (Manitz et al. 2013) is used for production planning. It consists of three planning levels, which are master production scheduling, material requirements planning and scheduling (see Figure 1). Production planning is done over a long horizon – ten weeks in this paper – and bases on demands. As demands are not known deterministically for the whole planning horizon in most applications, production planning is usually done on demand forecasts (see Herrmann 2011). The real demands generally deviate from the forecasts; this leads to both out-of-stock and excessive stock situations. Demand uncertainty has led to intensive research for the last decades. From early on, it was tried to consider uncertainty in the planning concepts, for instance by rolling planning. For an overview over these concepts to consider uncertainty, see (Herrmann and Englberger 2013).

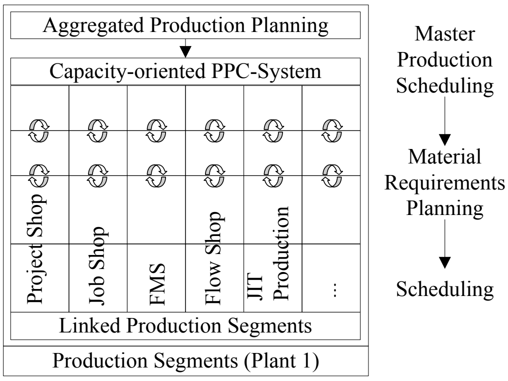

Figure 1: Hierarchical Production Planning (see (Günther and Tempelmeier 2012))

Over the last years, approaches of robust or stochastic optimisation have been in the focus of interest; these approaches are considered in this work. The remainder of this paper is structured as follows: firstly, a review of literature regarding stochastic optimisation for master production scheduling is given. Then, the test problem is described. Afterwards, the considered models for master production scheduling are explained. In the next sections, the simulation experiments and their results are described. At the end, a conclusion and an outlook are given.

LITERATURE REVIEW

(Escudero et al. 1993) propose a multi-stage stochastic production planning approach. Their studies show significant improvements compared to the conventional, deterministic approaches. (Mulvey et al. 1995) characterise the term of robust optimisation as trading off between solution quality and feasibility. To operationalize this trade off the objective function of their two-stage stochastic model is a weighted sum of a conventional cost function and an error variables function. Based on this approach, numerous two-stage stochastic models for aggregate production planning under uncertainty have been developed. (Yu and Li 2000) eliminate several absolute value functions from the error variables function to improve solving speed. Basing on this formulation, (Leung et al. 2007) propose a model for aggregate production planning regarding several production facilities, and costs for production, human labour, keeping inventories and adaption of

Proceedings 27th European Conference on Modelling and Simulation ©ECMS Webjørn Rekdalsbakken, Robin T. Bye, Houxiang Zhang (Editors)
ISBN: 978-0-9564944-6-7 / ISBN: 978-0-9564944-7-4 (CD)

personal capacities. (Al-e-Hashem et al. 2011) expand the model of (Yu and Li 2000) to a multiobjective optimisation model with the primary objective function regarding costs for production, labour including adaption of personal capacities, keeping inventory, transportation and backorders. The second objective function considers the maximum shortages among customer zones in all periods. (Zhang et al. 2011) develop a two-stage stochastic model that minimises annual labour cost, overtime cost, end product inventory cost and raw material inventory cost. (Scholl 2001) develops numerous models for robust production planning using different decision criteria in the objective functions and different modelling approaches. In numerical investigations, (Scholl 2001) concludes that compensation models with relative regret criteria are superior to other approaches in most cases (also see Herrmann and Englberger 2013). Based on his work, (Gebhard 2009) develops a concept for robust hierarchical production planning consisting of two planning levels. In numerical studies, (Gebhard 2009) shows that the robust approach is superior to an equivalent deterministic approach using a simple mathematical model representing basically an objective function and restrictions of a production system for evaluation.
Almost all of these investigations focus on the improvements of the objectives of master production scheduling, which is regularly a cost function. Implicitly, they assume that their master production schedules are realizable. Still, some planning parameters like resource consumptions caused by end products are used for master production scheduling but depend on planning decisions that are yet to be made at the time of master production scheduling. To the knowledge of the authors, robust master production planning never has been analysed in a planning hierarchy that comes close to the planning systems used in industrial applications. In this paper, the effects of robust production planning are evaluated using a planning hierarchy that is common in industrial applications.

TEST PROBLEM

To analyse the benefits of robust production planning, a part of the production of a company building high-voltage electronic devices in Regensburg is considered. This test problem includes five end products. The end products consist of numerous subassemblies and components on four disposition levels (as shown in Figure 2 for end product P1). The total number of products regarded in this case study is 82.

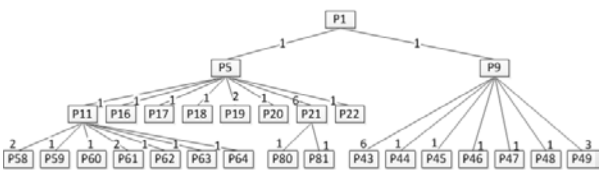

Figure 2: Bill of materials for end product P1

Each product's work plan has between two and six operations that need to be performed. As an example, the work plan for product P19 is displayed in Table 1.

Table 1: Work plan for product P19

Operation Number	Operation	Setup time $\left[\frac{\text{min}}{\text{lot}}\right]$	Operation time $\left[\frac{\text{min}}{\text{piece}}\right]$
1	Cutting	2	4
2	Turning	5	10
3	Milling	5	10
4	Grinding	3	5

These products are built on twelve production segments each consisting of one or several machines. Each production segment has normal capacity that can be used without extra costs, and additional capacity, which is more costly than normal capacity due to shift allowances, et cetera. The capacities of the production segments are listed in Table 2.

Table 2: Production Segments

Production Segment	Normal Capacity $\left[\frac{\text{hours}}{\text{week}}\right]$	Additional Capacity $\left[\frac{\text{hours}}{\text{week}}\right]$	Costs for Additional Capacity $\left[\frac{€}{\text{hour}}\right]$
Punching	336	168	10
Cleaning	224	112	10
Turning	560	280	10
Milling	560	280	10
Hardening	112	56	10
Isolating	112	56	10
Assembly	336	168	10
Testing	224	112	10
Broaching	112	56	10
Cutting	112	56	10
Grinding	448	224	10
Abrasive blasting	112	56	10

MASTER PRODUCTION SCHEDULING

Master production scheduling is performed via a deterministic and alternatively a robust version the model HPPLAN (Hauptproduktionsprogrammplanung) proposed in (Günther and Tempelmeier 2012) and (Manitz et al. 2013). The parameters and variables of the deterministic model HPPLAN are:

Parameters:

$b_{j,t}$ production capacity of production segment j in period t

$d_{k,t}$ demand for product k in period t

$f_{j,k,z}$ resource consumption on production segment j caused by product k in lead period z

h_k inventory costs for product k per unit and period

J number of production segments ($1 \le j \le J$)

K number of end products ($1 \le k \le K$)

T length of the planning horizon in weeks ($1 \le t \le T$)

$U_{j,t}^{max}$ maximum additional capacity for production segment j in period t

u_t costs for one unit of additional capacity in period t

z_k lead time for product k ($1 \le z \le Z_k$)

Variables:

$U_{j,t}$ used additional capacity in production segment j in period t

$x_{k,t}$ production quantity of product k in period t

$I_{k,t}$ inventory for product k at the end of period t

HPPLAN minimises costs for keeping inventory and using additional capacity in its objective function:

$$\text{Minimise } Z = \sum_{k=1}^{K}\sum_{t=1}^{T} h_k \cdot I_{k,t} + \sum_{t=1}^{T}\sum_{j=1}^{J} u_t \cdot U_{j,t}$$

The constraints of HPPLAN are:

- inventory balance constraint

$$x_{k,t} + I_{k,t-1} - I_{k,t} = d_{k,t} \ \ \forall\ 1 \le k \le K\,;\forall\ 1 \le t \le T$$

- restriction of production capacity

$$\sum_{k=1}^{K}\sum_{z=0}^{z_k} f_{j,k,z} \cdot x_{k,t+z} - U_{j,t} \le b_{j,t} \ \ \forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- restriction of additional capacity

$$U_{j,t} \le U_{j,t}^{max} \ \ \forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- non-negativity restrictions

$$x_{k,t}, I_{k,t}, U_{j,t} \ge 0 \ \ \forall\ 1 \le k \le K\,;\forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- determination of initial inventory

$$I_{k,0} = \text{given} \ \ \forall\ 1 \le k \le K$$

The deterministic model HPPLAN is transformed into the two-stage stochastic optimization model TSS-HPPLAN for robust master production planning. Demand uncertainty is represented via a set of demand scenarios Ω, where each scenario consists of the demands $\left(d_{k,t}^{s}\right)_{k=1,t=1}^{K\ \ T}$ (with $s \in \Omega$). The resulting production plan consists of a basic plan $x_{k,t}^{0}$ that is implemented immediately. After the demands of period $t = 1$ are known, the basic plan is modified with a compensation plan that increases $\left(x_{k,t}^{s+}\right)$ or reduces $\left(x_{k,t}^{s-}\right)$ the basic plan if necessary. The production quantities of period $t > 1$ are then $x_{k,t}^{0} + x_{k,t}^{s+} - x_{k,t}^{s-}$. In addition, $I_{k,t}^{s}$ and $U_{j,t}^{s}$ become scenario dependent. Master production scheduling is realized in a rolling planning environment. The replanning interval for TSS-HPPLAN is one period. Consequently, just the first period of every master production schedule is implemented. As there is no compensation plan for the first period, no compensations are ever realized; instead, a new basic plan is generated and realized every period (also see Alfieri and Brandimarte 2005). The objective function of TSS-HPPLAN minimises the expected costs under the assumption that all scenarios are even likely to occur. It sums up inventory costs, costs for the use of additional capacity and costs for changing production quantities (with cost coefficient c_t) as frequent changes of production quantities usually lead to additional costs (see Kimms 1998). The implementability constraint prevents that compensation plans react on demands that are not yet known at their implementation time (see Rockafellar and Wets 1991, Wets 1989). It says that if two scenarios are identical upon a period, their solutions have to be identical until then as well. The resulting model TSS-HPPLAN has the objective function:

$$\text{Minimise } Z = \frac{1}{|\Omega|}\sum_{s\in\Omega} Z_s$$

$$Z_s = \sum_{k=1}^{K}\sum_{t=1}^{T} h_k \cdot I_{k,t}^{s} + \sum_{t=1}^{T}\sum_{j=1}^{J} u_t \cdot U_{j,t}^{s} + \sum_{k=1}^{K}\sum_{t=1}^{T} c_t \cdot \left(x_{k,t}^{s+} + x_{k,t}^{s-}\right)$$

The constraints of TSS-HPPLAN are:

- inventory balance constraint

$$x_{k,t}^{0} + x_{k,t}^{s+} - x_{k,t}^{s-} + I_{k,t-1}^{s} - I_{k,t}^{s} = d_{k,t}^{s}$$
$$\forall\ s \in \Omega\ \forall\ 1 \le k \le K\ \forall\ 1 \le t \le T$$

- restriction of production capacity

$$\sum_{k=1}^{K}\sum_{z=0}^{z_k} f_{j,k,z} \cdot \left(x_{k,t+z}^{0} + x_{k,t+z}^{s+} - x_{k,t+z}^{s-}\right) - U_{j,t}^{s} \le b_{j,t}$$
$$\forall\ s \in \Omega\,;\forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- restriction of additional capacity

$$U_{j,t}^{s} \le U_{j,t}^{max} \ \ \forall\ s \in \Omega\,;\forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- non-negativity restrictions

$$x_{k,t}^{0}, x_{k,t}^{s+}, x_{k,t}^{s-}, \left(x_{k,t}^{0} + x_{k,t}^{s+} - x_{k,t}^{s-}\right), I_{k,t}^{s}, U_{j,t}^{s} \ge 0$$
$$\forall\ 1 \le k \le K\,;\forall\ 1 \le j \le J\,;\forall\ 1 \le t \le T$$

- determination of initial inventory

$$I_{k,0}^{s} = \text{gegeben} \ \ \forall\ s \in \Omega\ \forall\ 1 \le k \le K$$

- implementability constraint

$$x_{k,t}^{s+} = x_{k,t}^{s'+}, x_{k,t}^{s-} = x_{k,t}^{s'-} \ \forall\ 1 \le k \le K\ ; \forall\ 1 \le t \le T\ ;$$
$$\forall\ s,s' \in \left\{ \Omega | d_{k,1}^{s} = d_{k,1}^{s'} \right\}$$

SIMULATION

The test problem and the planning system are implemented in a simulation system that is comparable to the production planning systems used in industrial applications.

The primary objective of the production system is to minimise the tardiness of the fulfilment of customer orders. The secondary objective is to minimise the inventory levels of end products. To simulate demand uncertainty, a set Ω^0 of different customer order scenarios is built. Each scenario represents a realistic order situation. Each customer order scenario consists of a set O^s of customer orders. Each customer order o^s with $o^s \in O^s$ regards one product $k\left(o^s\right)$ with $1 \le k\left(o^s\right) \le K$, is due at the beginning of period $t\left(o^s\right)$ within the simulation horizon $1 \le t\left(o^s\right) \le T^{sim}$ and has a demand quantity $d\left(o^s\right)$. One of these scenarios $s^{CO} \in \Omega^0$ is realized in the simulation experiments. The other scenarios $\Omega = \Omega^0 \setminus s^{CO}$ are used for production planning.

Master production scheduling is solved using either the HPPLAN or the TSS-HPPLAN optimisation model. For a simulation horizon of T^{sim} weeks, master production scheduling is performed at the beginning of each week τ for all $1 \le \tau \le T^{sim}$. The master production schedule of the weeks $\left[\tau, \tau+1\right]$ is frozen, and with a planning horizon T of ten weeks the actual planning horizon for master production scheduling is $\left[\tau+2, ..., \tau+11\right]$.

The demand scenarios are $\left(d_{k,t}^{s}\right)_{k=1,t=1}^{K\ \ T}$ with $d_{k,t}^{s} = \sum_{o \in \left\{o^s \in O^s : k\left(o^s\right)=k \wedge t\left(o^s\right)=t\right\}} d\left(o\right)$. These demand scenarios are used for TSS-HPPLAN. For HPPLAN, a deterministic replacement scenario is built by using the mean values of the scenario specific demands $\left(d_{k,t} = \frac{\sum_{s \in \Omega} d_{k,t}^{s}}{\left|\Omega\right|}\right)_{k=1,t=1}^{K\ \ T}$.

The initial inventories $I_{k,0}$ for HPPLAN and TSS-HPPLAN (which refer to period $\tau+2$) are not known to the planning system at period τ. The expected inventories for period $\tau+2$ base on the current inventory levels $I_{k,\tau}$, all open customer orders from past periods $\mathrm{OrderBacklog}_k$, the expected customer orders $\mathrm{ExpectedDemand}_k$ and the production quantities $\mathrm{Production}_k$ during the frozen horizon. The initial inventory for master production scheduling is then

$$\begin{aligned} I_{k,0} = I_{k,\tau} \\ &- \mathrm{OrderBacklog}_k \\ &- \mathrm{ExpectedDemand}_k \\ &+ \mathrm{Production}_k \end{aligned}.$$

The results of master production scheduling are production quantities $x_{k,t}$, additional capacities per production segment $U_{j,t}$ and inventory levels $I_{k,t}$.

The production quantities as well as the additional capacity are then timely disaggregated as the period size for material requirements planning is days. As inventory levels are already regarded in master production scheduling, the master production schedule represents net requirements. For lot-sizing, the procedures of Groff and Silver-Meal are regarded as superior. As Groff is implemented in commercial planning systems regularly, it has been chosen for this investigations as well as just-in-time lot sizing. Material requirements planning is done at the beginning of each day for the upcoming 21 days. For scheduling, the priority rules first-in-first-out (FIFO) or slack (SL) are used. The produced goods are stored at the end of the day their production was finished in; they are available for customer order shipment or further production at the beginning of the next day.

To get statistically significant results, long-term simulation runs are executed. The warm-up period of the resulting series of tardiness and stock levels is cut off using the MSER-5 heuristic described in (White 1997) and (White, JR. et al. 2000). To evaluate the primary production objective of minimising tardiness, the tardiness $T\left(o^s\right)$ in days of each customer order $o^{s^{CO}}$ is logged. The overall mean customer order tardiness is $T_{mean} = \frac{\sum_{o \in O^{s^{CO}}} T\left(o\right)}{\left|O^{s^{CO}}\right|}$. To enable comparisons to inventory management, β service levels are computed additionally as $\beta = 1 - \frac{\sum_{o \in \left\{o^{s^{CO}} \in O^{s^{CO}} : T(o) > 0\right\}} d\left(o\right)}{\sum_{o \in O^{s^{CO}}} d\left(o\right)}$; this is identically to the β service levels used in inventory management. To evaluate the secondary production objective of minimising end product inventory levels, the inventory level $I_{k,t}$ of end products in pieces is logged each period. The overall average inventory level is $I_{mean} = \frac{\sum_{k=1}^{K} \sum_{t=1}^{T^{sim}} I_{k,t}}{K \cdot T^{sim}}$.

Generally, there are two factors that lead to tardiness: firstly, if the master production schedule underestimates future customer demand; secondly, if the production system cannot fulfil the master production schedule. To differ between those two factors, the degree to which a production system fulfils a master production schedule is measured here as follows: $x_{k,t}$ is the production quantity that should become available in period t according to the master production schedule. $x_{k,t}^{real}$ is the production quantity that actually becomes available. The fulfilment of the master production schedule up to period τ is $x_{k,\tau}^{fulfil} = \sum_{t=1}^{\tau} x_{k,t}^{real} - \sum_{t=1}^{\tau} x_{k,t}$. If $x_{k,\tau}^{fulfil} > 0$, more units of product k have been produced up to period τ then there should; if $x_{k,\tau}^{fulfil} < 0$, the production system has a backlog on the master production schedule. Both cases are in particular due to the use of static lead times for material requirements planning while the real lead times are variable. To analyse the mean fulfilment of the master production schedule, $x_{mean}^{fulfil} = \sum_{k=1}^{K} \sum_{\tau=1}^{T} x_{k,\tau}^{fulfil}$ is computed.

To determine variance and confidence intervals for the mean tardiness and inventory levels, the Overlapping Batch Means heuristic originally proposed by (Meketon and Schmeiser 1984) is used; the optimal batch size is determined using the heuristic of Song proposed in (Song 1996). The resulting confidence intervals with error probability $\alpha = 0{,}1$ (which is the probability that the averages are not within the confidence intervals) are $\left[CI_{\alpha}^{-}(T_{mean}), CI_{\alpha}^{+}(T_{mean})\right]$ and $\left[CI_{\alpha}^{-}(I_{mean}), CI_{\alpha}^{+}(I_{mean})\right]$.

The simulation model is implemented in Tecnomatix Plant Simulation 10.1; the optimization models are implemented and solved with IBM ILOG CPLEX Optimization Studio Version 12.5 on a DELL workstation with two Intel Xeon E5-2643 processors and 64 GB of RAM.

NUMERICAL RESULTS

The simulation parameters for the investigations are shown in Table 3.

Table 3: Simulation parameters

MPS model	$\{$HPPLAN,TSS-HPPLAN$\}$
$\lvert\Omega\rvert$	$\{5,10,20\}$
Lot-sizing	$\{$Just-In-Time, Groff$\}$
Scheduling	$\{$FIFO, SL$\}$

Table 4 shows the mean tardiness of the delivery of customer orders when using the master production scheduling models HPPLAN and TSS-HPPLAN with $\lvert\Omega\rvert = 10$, the lot-sizing procedure Just-In-Time and the Scheduling-Rule FIFO. When using HPPLAN, the mean tardiness is $2{,}65$ days. As the mean daily demand is $7{,}34$ units, the mean backlog is $19{,}45$ units. When using TSS-HPPLAN instead of HPPLAN, the mean tardiness is reduced to $0{,}46$ days, which results in a mean backlog of $3{,}38$ units. Table 5 shows the mean inventory levels of the analysis. Using TSS-HPPLAN, the mean inventory levels are $14{,}27$ units, while they are $5{,}4$ units when using HPPLAN. In consequence, TSS-HPPLAN reduces the mean backlog by $16{,}07$ units while mean inventory levels increase by just $8{,}87$ units.

Table 4: Customer order tardiness and service level

MPS model	CI_{α}^{-}	T_{mean}	CI_{α}^{+}	β
HPPLAN	2,49	2,65	2,8	45,34%
TSS-HPPLAN	0,37	0,46	0,55	85,25%

Table 5: Inventory levels

MPS model	CI_{α}^{-}	I_{mean}	CI_{α}^{+}
HPPLAN	5,14	5,4	5,66
TSS-HPPLAN	13,95	14,27	14,6

Table 6: Master production schedule fulfilment

MPS model	CI_{α}^{-}	x_{mean}^{fulfil}	CI_{α}^{+}
HPPLAN	1,38	1,4	1,43
TSS-HPPLAN	1,17	1,22	1,28

These results show that TSS-HPPLAN builds up inventory to cope with uncertain demand. As master production scheduling at week τ determines the production quantities of week τ, but does not yet know the demands in week τ, the only possibility to hedge against demand uncertainty is to build up enough stock to be able to deliver all demand scenarios. If the realized scenario exceeds all demand scenarios or if production cannot fulfil the master production schedule on time, out-of-stock situations can occur. TSS-HPPLAN leads to a significant reduction of tardiness though the master production schedule fulfilment is significantly lower compared to HPPLAN (see Table 6).

When using the slack rule for scheduling instead of FIFO, tardiness decreases while inventory levels increase for both MPS models. When using TSS-HPPLAN, T_{mean} drops $0{,}26$ days (which is equivalent to a reduction of the mean backlog of $1{,}91$ units) while I_{mean} increases $4{,}18$ units compared to the investigation using TSS-HPPLAN and FIFO. When using HPPLAN, T_{mean} drops $0{,}61$ days ($4{,}48$ units) while I_{mean} increases $1{,}2$ units compared to the investigation using HPPLAN and FIFO (see Table 7 and Table 8).

Table 7: Customer order tardiness and service level

MPS model	CI_{α}^{-}	T_{mean}	CI_{α}^{+}	β
HPPLAN	1,9	2,04	2,17	53,59%
TSS-HPPLAN	0,15	0,2	0,25	92,69%

Table 8: Inventory levels

MPS model	CI_α^-	I_{mean}	CI_α^+
HPPLAN	6,36	6,6	6,85
TSS-HPPLAN	18,04	18,45	18,87

The reason for the steeper drop of tardiness when using TSS-HPPLAN can be explained when regarding the master production schedule fulfilment shown in Table 9. In contrast to the previous analysis with the FIFO scheduling rule, now the fulfilment of the master production schedule is almost even as shown in Table 9. Under these even conditions regarding the fulfilment, TSS-HPPLAN reduces the mean backlog by $13{,}51\text{ units}$ while it increases inventory levels by $11{,}85\text{ units}$.

Table 9: Master production schedule fulfilment

MPS model	CI_α^-	x_{mean}^{fulfil}	CI_α^+
HPPLAN	1,4	1,42	1,44
TSS-HPPLAN	1,38	1,41	1,44

When using the Groff procedure for lot-sizing and the slack rule for scheduling, tardiness increases and inventory levels sink (see Table 10 and Table 11) compared to using JIT lot-sizing and the slack rule for scheduling.

Table 10: Customer order tardiness and service level

MPS model	CI_α^-	T_{mean}	CI_α^+	β
HPPLAN	2,26	2,4	2,55	51,29%
TSS-HPPLAN	0,24	0,3	0,36	90,13%

Table 11: Inventory levels

MPS model	CI_α^-	I_{mean}	CI_α^+
HPPLAN	6,2	6,45	6,7
TSS-HPPLAN	17,23	17,65	18,07

Tardiness increases $0{,}36\text{ days}$ for HPPLAN and $0{,}1\text{ days}$ for TSS-HPPLAN; inventory levels decrease $0{,}15\text{ units}$ for HPPLAN and $0{,}8\text{ units}$ for TSS-HPPLAN. The decreases of inventory levels are small due to the inventory levels caused by lot-sizing. The steeper increase for TSS-HPPLAN is due to the lower fulfilment of the master production schedule (see Table 12).

Table 12: Master production schedule fulfilment

MPS model	CI_α^-	x_{mean}^{fulfil}	CI_α^+
HPPLAN	0,27	0,41	0,55
TSS-HPPLAN	-0,08	0,07	0,22

The above investigations show that TSS-HPPLAN reduces tardiness significantly compared to HPPLAN. When using TSS-HPPLAN, tardiness and inventory levels largely depend on the number of scenarios $|\Omega|$ used for planning. As shown in Table 13 and Table 14, increasing the number of scenarios from 5 to 20 reduces mean tardiness from $0{,}86\text{ days}$ $(6{,}31\text{ units})$ to $0{,}25\text{ days}\,(1{,}84\text{ units})$, while it increases the mean inventory from $11{,}61\text{ units}$ to $17{,}04\text{ units}$.

Table 13: Customer order tardiness and service level

$\|\Omega\|$	CI_α^-	T_{mean}	CI_α^+	β
5	0,72	0,86	0,99	77,04%
10	0,37	0,46	0,55	85,25%
20	0,19	0,25	0,31	91,03%

Table 14: Inventory levels

$\|\Omega\|$	CI_α^-	I_{mean}	CI_α^+
5	11,24	11,61	11,99
10	13,95	14,27	14,6
20	16,43	17,04	17,65

CONCLUSION AND OUTLOOK

In this paper, robust master production scheduling is analysed in an industrially relevant planning environment. A deterministic model for master production scheduling is extended to a stochastic model. Both models are implemented in a simulation model that represents a production planning and control system as it is commonly used in commercial planning systems and a production system basing on a real production system. The analysis shows that tardiness in the delivery of customer orders depends on the master production schedule at one hand and the fulfilment of the master production schedule on the other hand. To determine the effects caused by robust master production scheduling, an indicator is introduced to determine the degree of fulfilment of the master production schedule. The results of the analysis show that tardiness can be reduced significantly by the use of a stochastic model for master production scheduling while end product inventory levels increase significantly.

Future research should address the ability to fulfil master production schedules as well as the run time to solve robust models for master production scheduling.

REFERENCES

Al-e-Hashem, S.M.J.M.; H. Malekly and M.B. Aryanezhad. 2011. "A multi-objective robust optimization model for multi-product multi-site aggregate production planning in a supply chain under uncertainty." *International Journal of Production Economics* 134, 28–42.

Alfieri, A. and P. Brandimarte. 2005. "Stochastic Programming Models for Manufacturing Applications". In *Design of advanced manufacturing systems*, Andrea Matta, Quirico Semeraro (Eds.). Springer, Dordrecht.

Drexl, A.; B. Fleischmann; H.-O. Günther; H. Stadtler and H. Tempelmeier. 1994. "Konzeptionelle Grundlagen kapazitätsorientierter PPS-Systeme." *Zeitschrift für Betriebswirtschaftliche Forschung* 46, 1022–1045.

Escudero, L.; P. Kamesam; A. King and R. Wets. 1993. "Production planning via scenario modelling." *Annals of Operations Research* 43, 311–335.

Gebhard, M. 2009. "Hierarchische Produktionsplanung bei Unsicherheit." Gabler, Wiesbaden.

Günther, H.-O. and H. Tempelmeier. 2012. "Produktion und Logistik." Springer, Berlin.

Hax, A.C. and H.C. Meal. 1975. "Hierarchical Integration of Production Planning and Scheduling". In *Logistics*, Murray A. Geisler (Ed.). North Holland, Amsterdam.

Helber, S.; F. Sahling and K. Schimmelpfeng. 2012. "Dynamic capacitated lot sizing with random demand and dynamic safety stocks." *OR Spectrum*.

Herrmann, F. 2011. "Operative Planung in IT-Systemen für die Produktionsplanung und -steuerung. Wirkung, Auswahl und Einstellhinweise." Vieweg + Teubner, Wiesbaden.

Herrmann, F. and J. Englberger. 2013. "Robuste Optimierung zur Produktionsprogrammplanung". In *Divergierende Forschungsansätze zur Produktionsplanung und -steuerung*, Thorsten Claus, Frank Herrmann, Michael Manitz (Eds.). Springer, Berlin.

Kimms, A. 1998. "Stability Measures for Rolling Schedules with Applications to Capacity Expansion Planning, Master Production Scheduling, and Lot Sizing." *Omega* 26, No. 3, 355–366.

Leung, S.C.; S.O. Tsang; W. Ng and W. Yue. 2007. "A robust optimization model for multi-site production planning problem in an uncertain environment." *European Journal of Operational Research* 181, 224–238.

Manitz, M.; F. Herrmann and J. Englberger. 2013. "Ein hierarchisches Planungskonzept zur operativen Produktionsplanung und -steuerung". In *Divergierende Forschungsansätze zur Produktionsplanung und -steuerung*, Thorsten Claus, Frank Herrmann, Michael Manitz (Eds.). Springer, Berlin.

Meketon, M.S. and B. Schmeiser. 1984. "Overlapping Batch Means: Something for Nothing?". In *Proceedings of the 1984 Winter Simulation Conference*.

Mulvey, J.; R. Vanderbei and S. Zenios. 1995. "Robust Optimization of Large-Scale Systems." *Operations Research* 43, 264–281.

Rockafellar, R. and R. Wets. 1991. "Scenarios and Policy Aggregation in Optimization under Uncertainty." *Mathematics of Operations Research* 16, No. 1, 119–147.

Scholl, A. 2001. "Robuste Planung und Optimierung. Grundlagen - Konzepte und Methoden - experimentelle Untersuchungen". Physica-Verlag, Heidelberg.

Song, W.T. 1996. "On the estimation of optimal batch sizes in the analysis of simulation output." *European Journal of Operational Research, No.* 88, 304–319.

Wets, R. 1989. "The Aggregation Principle in Scenario Analysis and Stochastic Optimization". In *Algorithms and Model Formulations in Mathematical Programming*, S.W Wallace (Ed.). Springer, Berlin.

White, K.P. 1997. "An Effective Truncation Heuristic for Bias Reduction in Simulation Output." *SIMULATION* 69, No. 6, 323–334.

White, K.P., JR.; M.J. Cobb and S.C. Spratt. 2000. "A Comparison of five Steady-State Truncation Heuristics for Simulation". In *Proceedings of the 2000 Winter Simulation Conference*.

Yu, C. and H. Li. 2000. "A robust optimization model for stochastic logistic problems." *International Journal of Production Economics* 64, 385–397.

Zhang, X.; M. Prajapati and E. Peden. 2011. "A stochastic production planning model under uncertain seasonal demand and market growth." *International Journal of Production Research* 49, No. 7, 1957–1975.

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