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Linking deterministic aggregate production planning with a stochastic simulation model using a planned utilisation factor

Integration einer deterministischen Jahresplanung mit einem stochastischen Simulationsmodell durch einen Planauslastungsfaktor

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Abstract: We consider a production system with a flow-shop structure inspired by a production company operating in the automotive sector with forecast errors. A hierarchical production planning approach is carried out in a simulation model whereby the periodically performed aggregate planning is implemented by a MIP-solver. To account for the stochastic behaviour of real production systems a planned utilization factor is introduced in the MIP model for the aggregate planning. In a simulation study, the influence of this planned utilization factor on overall costs and the influence of forecast errors on the optimal planned utilization are investigated for seasonal and constant monthly forecast / demand patterns. We identify a high cost reduction potential with implementing this planned utilization factor and for a specific scenario optimal values are derived. Furthermore, the study shows that higher forecast errors lead to lower optimal planned utilization values.

1 Literature Review

In production planning and control, hierarchical decision models with decision levels differing in time horizon and decision variables are widely used. For basic problem formulation see Hax and Meal (1975), Meal (1984), Schneeweis (2002) and Hopp and Spearman (2008). Especially the MRPII concept (Manufacturing resource planning), as for example presented in Hopp and Spearman (2008), is a structured approach which is widely used. It consists of three planning levels: long-term planning (strategy), intermediate planning (tactical) and short term control (operational). The long-term planning involves the three functions: forecasting, resource planning and aggregate planning. The aggregate planning determines appropriate levels of production, inventory and staffing (internal-capacity, external-capacity and overtime). According to Hopp and Spearman (2008), optimization techniques such as linear (LP) or mixed integer programming (MIP) are used to solve the aggregate planning optimization problem. Hax and Meal (1975), Gfrerer and Zäpfel (1995) and Zäpfel (1996) present respective models for aggregate planning. The main functions of the mid-term planning are master production scheduling (MPS), which compares the production plan with the actual customer orders, and material requirements planning (MRP) which identifies a list of production orders (see Hopp and Spearman 2008 for MPS and Orlickey 1975 for MRP). The short-term planning conducts scheduling and dispatching tasks (see Panwalkar and Iskander 1977) for production orders and available resources.

The hierarchical structuring of the production planning and control decisions has the advantage of splitting up different decision variables to their respective time horizons and therefore ensures their manageability. However, the restrictive structure of this approach, meaning that the upper level decisions are the constraints for lower level decisions and the feedback loop, that actual inventory levels and scheduled receipts influence upper decisions levels having shortfalls. Some examples of studies on the influence on the interaction of different planning levels are Framin et al. (2000) discussing the impact of the short term control on the midterm planning method CONWIP or Dauzere-Peres and Lasserre (1994) providing an integrated planning and scheduling approach. One of the occurring problems is that decision problems often used for the long term level are deterministic (see Schneeweis 2002 and Hax and Meal 1975) but the real production system faces a set of stochastic influences. One aspect of this problem is discussed in the current study.

2 Introduction

We investigate the influence of optimizing the long term production plan (including production amount and capacity levels) assuming a deterministic production system and applying it to a stochastic production system which fulfils the MPS, MRP and dispatching functionality according to the MRPII concept. Processing times, order amount and order arrivals are random. In detail, a planned utilization factor η, which defines the internal utilization of the production system, is included in the long term MIP problem for aggregate planning. This planned utilization factor defines the internal production system utilization. Its effect on service level and overall costs including capacity, tardiness and inventory costs is studied. The hierarchical production planning approach is modelled with a simulation generator (see Hübl et al. 2011 and Felberbauer et al. 2012). A rolling horizon planning is conducted for the long and mid-term planning level. For the aggregate planning (MIP problem) we build an interface between the simulation software AnyLogic© and the exact solver CPLEX©. The aggregate planning problem is solved three times per year, via function call within the simulation model, for a planning horizon of twelve month T. There is a cross data exchange between the simulation model and the MIP-Solver. The MIP-Solver uses transaction (inventory levels) and master data (forecasts, processing times and shift systems) from the simulation model and returns the optimal production programme (inventory levels, production amount per month and internal and external capacities per month of the machine groups). The production system structure is similar to that of many automotive suppliers. However, it is a streamlined version of such systems which clearly restricts the findings in this study. The streamlined structure, including customer demand pattern, bill of material, routing information and planning methods has been created based on project knowledge of past applied studies in this industry. Based on the generic simulation model, the same study can be conducted using real company data to fill the database whereby such data is available in common ERP (enterprise resource planning) or MES (manufacturing execution system) systems.

By applying a numerical study, we investigate how much capacity flexibility is needed in the aggregate planning (MIP model) to reach an appropriate operational service level with respect to minimal overall costs. In a second study, we observe how the optimal planned utilization factor η_{opt} changes by an increasing forecast error. The forecast error incorporates the stochastic difference between deterministic monthly order rates from forecast and the stochastic realized monthly order rates in the simulation model. In further research we would like to create analytic models where the planned utilization factor η can be calculated according to the customer pattern and compare the results of the analytic model with the numerical study.

3 Model Description

3.1 Simulation Model

For the simulation study, a generic scalable simulation model is used, similar to the simulation study in Felberbauer et al. (2012). The core concept of the scalable simulation model is presented in Hübl et al. (2011) which explains the parameterization by a database. Thereby, it is possible to define different simulation scenarios without any adaption of the simulation model (programmed in Anylogic 6.9) itself. For a detailed description of the simulation modules compare, Felberbauer et al. (2012) and Hübl et al. (2011).

3.2 Aggregate Planning

We model the aggregate planning as a mixed integer problem MIP by employing the following decision variables. $x_{pt} \geq 0$ is the optimal production programme of sales product p out of P sales products in time period t. $K_{tj}^{e} \geq 0$ is the capacity of machine group j in time period t which is processed by an external company, is able to provide the required technology of machine group j out of J machine groups. Finally, the binary decision variables S_{tjs} are introduced for setting the applied shift plan and therefore the available internal capacity per machine group j and time period t. The optimal production programme x_{pt} and the respective inventory levels $l_{pt}$are disaggregated from months into days and used in the MRP-Planning approach (mid-term planning) of the simulation, which is calculated daily. Additionally, the optimal production programme x_{pt} is used as input for the MPS. In our model, the Gregorian calendar of 2013 is used and two shift plan models (five days and two shifts; five days and three shifts, per week) are available. The internal capacity per machine group, month t, and shift plan s, K_{tjs}^{i} relies on the respective shift plan and the calendar of the considered year. The selected shift plan S_{tjs} out of S shift plan possibilities and the external capacity K_{tj}^{e} per machine group j and time period t is applied and respectively outsourced according to the MIP results.

$$Min\sum_{t=1}^{T}\sum_{j=1}^{J}\left(K_{t,j}^{e}c^{e}+\sum_{s=1}^{S}K_{t,j,s}^{i}c^{i}S_{t,j,s}\right)+\sum_{p=1}^{P}c^{h}l_{pt} \tag{1}$$

$$\sum S_{t,j,s}=1 \qquad \begin{array}{l}\mathrm{t}=1,\ldots,\mathrm{T}\\ \mathrm{j}=1,\ldots,\mathrm{J}\end{array} \tag{2}$$

$$\sum_{p=1}^{P}x_{p,t}a_{p,j}\leq\eta\sum_{s=1}^{S}K_{t,j,s}^{i}S_{t,j,s}+K_{t,j}^{e} \qquad \begin{array}{l}\mathrm{t}=1,\ldots,\mathrm{T}\\ \mathrm{j}=1,\ldots,\mathrm{J}\end{array} \tag{3}$$

$$l_{p,0}=l_{p}^{s} \qquad t=1,\ldots,T \tag{4}$$

$$l_{p,t}=l_{p,t-1}+x_{p,t}-F_{p,t} \qquad t=1,\ldots,T \tag{5}$$

$$l_{p,t},x_{p,t}\geq 0 \qquad \begin{array}{l}p=1,\ldots,P\\ t=1,\ldots,T\end{array} \tag{6}$$

$$K_{t,j}^{e}\geq 0 \qquad \begin{array}{l}t=1,\ldots,T\\ j=1,\ldots,J\end{array} \tag{7}$$

$$S_{t,j,s}\in\{0,1\} \qquad \begin{array}{l}t=1,\ldots,T\\ j=1,\ldots,J\\ s=1,\ldots,S\end{array} \tag{8}$$

The objective function (1) minimizes the costs of internal / external capacity (at cost rate c^i and c^e for machine group *j* respectively) and the holding costs (holding costs rate per day c^h) which accrue by fulfilling the required demand. Due to constraints (2) only one shift plan can be applied for one machine group in one time period. Constraints (3) ensure that the capacity needed to produce the optimal production programme on the machine groups is lower or equal to the available capacity of internal and external resources. The external capacity is unlimited and the internal available capacity per machine group is dependent on the applied shift plan and the planned utilization factor η. The planned utilization factor is a real number between zero and one and its relevance is discussed in 3.5. The actual inventories of the simulation for all sales products l_p^s are defined as start inventories $l_{p,0}$ for the aggregate planning in constraints (4). Constraints (5) ensure that the required demand per period is fulfilled by the optimal production programme and the delta of the inventory of period *t-1* and period *t*. Finally, the constraints' (6)-(8) define the decision variables.

4 Problem Description

4.1 Production System Structure

The modelled production system follows a flow shop structure inspired by a production company operating in the automotive sector. The flow shop consists of six machines (M1-M6) which are arranged in three machine groups corresponding to production, assembly and packaging. In each group there are two individual machines which are technologically identical.

Figure 1 shows the bill of material (BOM) and the low level code (LLC). The arrows indicate which child item is required to produce one parent item and the cardinality in the arrows states the required number of materials. The materials in LLC 3 are purchased parts and in our study they are always available. All items as well as materials 20, 21, 30, 31 are MRP planned.

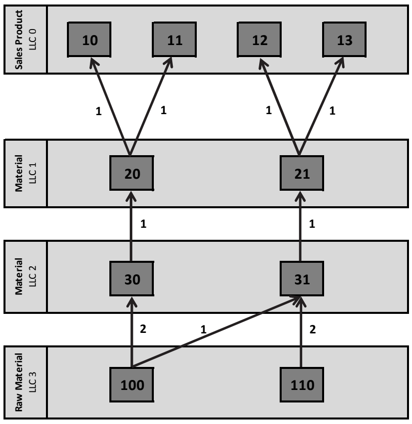

Figure 1: *Bill of Material*

Items1x are produced on machine group MG3 (packaging), items 2x are produced on machine group MG2 (assembly), and items 3x are produced on machine group MG1 (production). Generally, the production orders generated by the MRP-planning algorithm are sorted by the modified earliest due date (MEDD) dispatching rule. Each processing step requires a random processing time with an expected value E[p]=10 and a variance Var[p]=1. The expected value and the variance of the independent and identically lognormal distributed processing time is equal for all items and machine-routing-combinations.

4.2 Forecast / Demand Patterns

Two different forecast / demand patterns are considered. The overall forecast amount F_p per year and sales product is a deterministic value and is equal for all investigated scenarios. In this paper, two different forecast / demand patterns are considered. In the first scenario, the forecast per sales product and month is constant and is calculated according to $F_{p,t} = \frac{F_p}{T}$. Note that T is the number of month in a year, thus 12. The second forecast / demand pattern follows a seasonal sinus-demand-function. The phase shift of the sinus function is six time periods, therefore the forecast per month decreases during the first three time periods. The amplitude for the seasonal forecast pattern is $0.5\frac{\mathrm{F_p}}{\mathrm{T}}$ and the investigated time periods are again 12 months. The first row of Table 1 shows the seasonal forecast of the sales products 10 and 12; the second for product 11 and 13.

Table 1: *Seasonal demand*

Month	1	2	3	4	5	6	7	8	9	10	11	12
10/12	1,000	750	567	500	566	1,000	1,250	1,433	1,500	1,433	1,500	1,433
11/13	1,500	1,125	850	750	1,000	1,250	1,433	1,500	1,433	1,500	1,433	1,875

For both forecast / demand patterns the random value of demand per sales product p and time period t is $D_{p,t}$. The forecast error is an identically independent lognormal-distributed random variable with an expected value $\mathrm{E}[\mathrm{D}_{p,t}] = F_{p,t}$ and standard deviation of $\sigma_{D_{p,t}} = \alpha F_{p,t}$ for each sales product. Forecast error parameter α defines the quality of the forecast. The actual amount per order and item o_p is lognormal distributed with expected value $E[o_p] = 10$ and variance $Var[o_p] = 1.5$ for sales products 10 and 12, as well as expected value $E[o_p] = 15$ and variance $Var[o_p] = 2.5$ for items 11 and 13. For all scenarios the overall forecast amount F_p of sales products 10 and 12 is 12,000 pieces for each and 18,000 pieces for sales products 11 and 13 respectively.

4.3 Preliminary Study - Planned Internal Utilization Factor η

In a preliminary study (stable forecast-demand pattern, $\mathrm{E}[\mathrm{D}_{pt}] = 0$ and $\sigma_{D_{p,t}} = 0$), a low service level and overall cost performance has been identified when applying the standard long range planning (integrating a mixed integer problem for the calculation of an optimal production programme in the simulation model). The MIP-model tries to reduce capacity costs by adapting shift models, outsourcing and make to stock decisions. These decisions, based on the deterministic production system assumption lead to problems with the service level performance and overall costs in the stochastic environment of the simulation model, which mimics the real world production system. In this preliminary study, a service level of 1.6 % is found, which results in high tardiness costs. In detail, the problem is that the mixed integer problem provides too less internal capacity (utilization of the internal production system is 100%), so the production system has no chance to react on the stochastic customer demand. To deal with this problem efficiently, the planned utilization factor η is implemented into the mixed integer model of the long range planning, which provides capacity flexibility within the internal production system. The planned utilization factor η defines the planned internal production system utilization.

5 Numerical Study

5.1 Experiment Design

The performance measures for all studies conducted are the average overall costs per day separated into inventory, tardiness, internal capacity and external capacity costs. To avoid situations with seemingly low costs, but only due to excessively delaying customer orders, the tardiness costs are corrected at the end of the simulation run. Therefore, all customer orders that cannot be satisfied at the end of the simulation time are penalized due to their tardiness. The ratio of the inventory cost rate to the tardiness cost rate is chosen to be 1:19 (see also Axsäter 2000 for details on this ratio). The ratio of the internal and external capacity costs is 1:2.1 (€50 per hour internal €105 per hour for external capacity). The holding costs are increasing with a decreasing low level code and are €0.5 for items 1x, €0.2 for materials 2x and €0.1 for materials 3x per day and piece. In the experiments we simulated for four whole years with the above described annual forecast / demand behaviour are analysed, whereby the first year is the warm up time of the simulation model and therefore excluded from the analysis. Each run is replicated 20 times to account for stochastic variance.

5.2 Numerical Study - Planned Internal Utilization Factor η

Part one of the numerical study investigates the influence of the planned utilization factor η for constant and seasonal demand pattern. Figure 2 shows service level [%] and overall costs [€] with respect to the planned utilization factor η which is equivalent to the internal production system utilization (long dashed line → overall costs; short dashed line → service level).

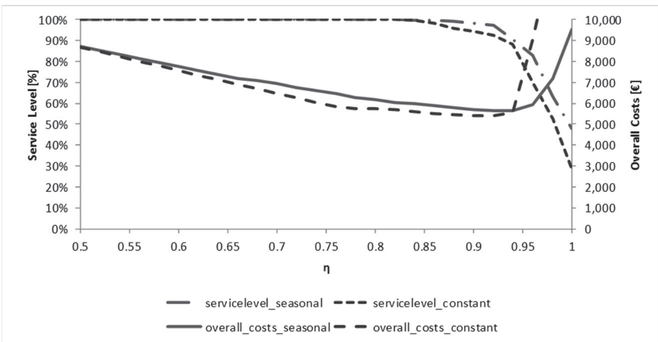

Figure 2: *Comparison of service level and overall costs for the constant and seasonal forecast / demand pattern*

The optimal planned utilization factor η_{opt} for the constant forecast / demand pattern is 0.92 with €5,388 overall costs and a service level of 92.3%. High production system utilization (η ≥ 0.95) leads to high overall costs, due to the high tardiness costs, and respectively to a poor service level performance. For low production system utilization (η ≤ 0.85), the service level performance is constantly 100%. The overall costs are decreasing with increasing production system utilization due to the decline in the need of external capacity which is more expensive per hour than the internal one.

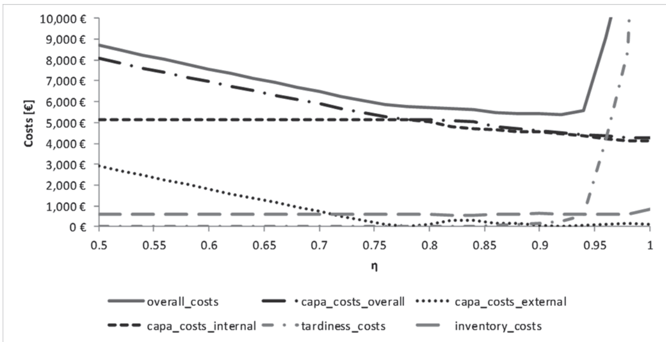

Figure 3: *Single parts of overall costs for the constant demand pattern*

Figure 3 shows the single parts of the overall costs for the constant demand pattern. The internal capacity costs are rather constant for the production system utilization range 50% to 80 %. Within that range the claimed flexibility is only reachable with a three shift model for all months and additional external capacity. The external capacity costs decrease with an increasing production system utilization up to 75%. From that point on, the external capacity costs are nearly always zero. The overall capacity costs are decreasing with increasing production system utilization. Furthermore, Figure 2 shows that the tardiness costs are responsible for the sharp increase of the overall cost for a production system utilization of more than 95%. Inventory costs increase with respect to high production system utilizations even though the finished good inventory (FGI) decreases. The reason for this is the surge of Work in Progress (WIP).

Seasonal forecast / demand pattern

Figure 2 shows the overall cost and service level results of the seasonal demand pattern (solid line → overall costs; chain dotted line → service level).

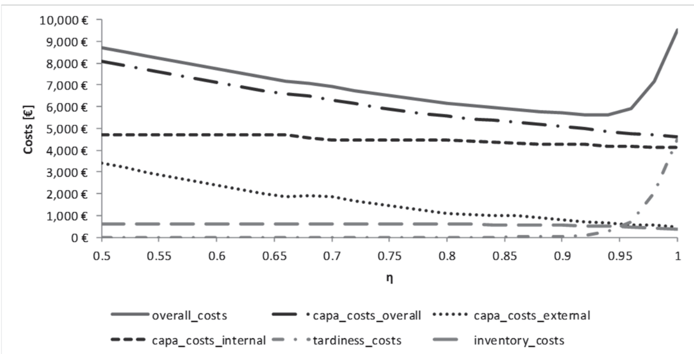

Figure 4: *Single parts of overall costs for the altering planned utilization factor η for the seasonal demand pattern*

The optimal planned utilization factor η_{opt} for the seasonal forecast / demand pattern is again 0.92 with €5,625 overall costs and a service level of 97.1%. Generally the service level, the costs and the inventory (FGI and WIP) have a quite similar behaviour for the altering planned utilization factor as in the constant demand pattern. But there are also some differences: The constant demand pattern has lower overall costs for the optimal planned utilization factor η_{opt}. In the seasonal demand pattern, the overall capacity costs are higher due to the higher amount of external capacity needed as you can see when you compare Figure 3 with Figure 4.

For high production system utilization, we found that in the seasonal demand pattern, the required capacity per machine group is changing from 1.3 to 3.9 required shifts per month. In the constant forecast / demand pattern, the required capacity is constant: 2.6 shifts per month. In the constant case with a high planned utilization, the MIP-model switches between three and two shifts and no external capacity is required. In the seasonal demand pattern, the MIP model tries to adapt the internal and external capacity according to the required capacity per month. The higher external capacity of the seasonal demand pattern has a positive influence on the overall costs and service level performance for high production system utilization as shown in Figure 2.

5.3 Numerical Study – Influence of the Forecast Error

In the second numerical study, the optimal overall costs and the optimal planned utilization factor η_{opt} are studied for different forecast error deviation factors α. The range of α is between 0 and 0.5 and the expected value of the actual monthly demand is kept at $\mathrm{E}[\mathrm{D}_{p,t}] = F_{p,t}$.

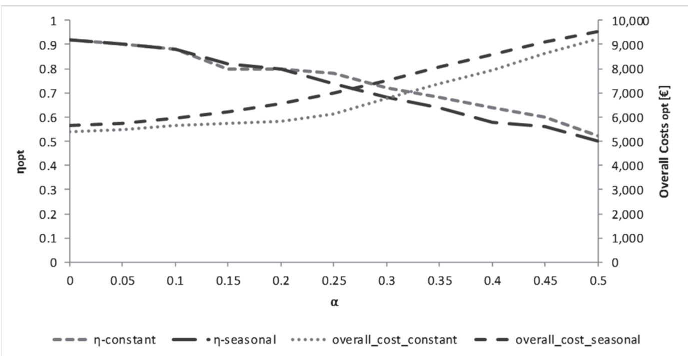

Figure 5: *Comparison of service level and overall costs for the altering forecast error deviation factor α for the constant and seasonal forecast / demand pattern*

The study shows that the overall costs of both, the constant and the seasonal demand pattern, have a positive correlation to α. The overall cost of the seasonal forecast / demand -pattern are higher than the ones of the constant pattern. For low α-factors, the optimal production system utilization η_{opt} of the constant and the seasonal demand pattern is similar. For higher deviations of the forecast error, the seasonal demand pattern needs more flexibility than the constant one.

6 Results

Additionally, to the presented results in the numerical studies, managerial insights can be formulated. Generally, the studies show that an aggregate planning without the consideration of a planned utilization factor would lead to high overall costs and a poor service level performance. The implementation of the planned utilization factor accounts for the stochastic behaviour of the real production system built in the simulation model. Furthermore, it is shown that excessive internal production system utilization runs the risk of high overall costs. Additionally, low service level would cause lost sales due to unsatisfied customers, which is not considered in our studies. Another finding is that a good forecast quality leads to a higher production system utilization and therefore lowers overall costs.

References

Axsäter, S.: Inventory control. Bosten, Dordrecht London: Kluwer Academic Publisher 2000.

Dauzere-Peres, S.; Lasserre, J.: An Integrated Approach in Production Planning and Scheduling. Lecture Notes in Economics and Mathematical Systems (1994)

Felberbauer, T.; Altendorfer K.; Hübl, A.: Using a scalable simulation model to evaluate the performance of production system segmentation in a combined mrp and kanban system. Proceedings of the 2012 Winter Simulation Conference, Berlin (Germany), 2012.

Framinan J., Ruiz-Usano R., Leisten R. Input control and dispatching rules in a dynamic CONWIP flow-shop. International Journal of Production Research 38 (2000), pp. 4589-4598.

Gfrerer, H.; Zäpfel G.: Hierachical model for Production planning in the case of uncertain demand. European Journal of Operational Research 86 (1995), pp. 142-161.

Hax, A.; Meal H.: Hierarchical integration of production planning and scheduling. TMS Studies in Management Science 1 (1975), pp. 53-69.

Hopp, W.; Spearman, M.: Factory physics, 3. ed., Boston: McGraw-Hill 2008.

Hübl, A.; Altendorfer, K.; Jodlbauer, H.; Gansterer, M.; Hartl R.: Flexible model for analysing production. Proceedings of the 2011 Winter Simulation Conference, Phoenix (USA), 2011, pp. 1554-1565.

Meal, H.: Putting production decisions where they belong. Harvard Business Review 62 (1984) 2, pp. 102-111.

Orlicky, J.: Material requirements planning. The new way of life in production and inventory management. New York: McGraw-Hill 1975.

Panwalkar, S.; Iskander W.: A survey of scheduling rules. Operations Research 25 (1997) 1, pp. 45-61,

Schneeweiß, C.: Einführung in die Produktionswirtschaft, 8. ed. Berlin: Springer series 2002.

Zäpfel, G.: Production Planning in the case of uncertain individual demand. Extension for an MRP. International Journal of Production Economics (1996) 26, pp. 257-264.