SIMULATION BASED CLEARING FUNCTIONS FOR A MODEL OF ORDER RELEASE PLANNING

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ABSTRACT

In capacitated production systems at high utilization there exists a nonlinear relationship between the orders which are in process and the output. This nonlinear relationship can be described by nonlinear Clearing Functions. We show how a Clearing function will be estimated and integrate it into a model of order releases planning. We compare our model with two inventory management policies under different demand conditions.

INTRODUCTION

Most currently commercially used Enterprise Resource Planning (ERP) and Production Planning and Control (PPC) systems decompose the overall planning problem into subproblems, e.g. the hierarchical production planning proposed by (Hax and Meal 1975). This leads to the master production scheduling, material requirement planning (MRP), with the key components net demand calculation and lot sizing, and the scheduling. In the PPC systems which are used in the industry, there is partly no consideration of limited capacities, such as in the lot sizing policy of Groff. The lead time is crucial for the assessment of exceeding capacities. The widely used MRP procedure (Orlicky 1975; Vollmann et al. 2005) uses fixed lead times to schedule work releases. Also the models of the master production scheduling and aggregate production planning imply linear and partly even fixed relationships between the workload and the lead times. Measurements of the actual lead times indicate a nonlinear relationship between the lead time and the workload in a capacitated production system. Methodologically this nonlinear relationship can be verified by queuing models (Hopp and Spearman 2001). Hence the lead time depends on the systems workload, which in turn is determined by the assignment of work to resources by the planning models.

Different approaches integrate the dependency between lead times and resource utilization in LP models. The first approaches of (Lautenschläger and Stadtler 1998; Spitter et al. 2005) relax the use of lead times and the approaches of (Ettl et al. 2000; Voss and Woodruff 2003) integrate the workload. Finally, the relationship between the workload and lead times is expressed by nonlinear Clearing Functions (CF), e.g. (Asmundsson et al. 2006). This Clearing Function approach is the focus of this paper.

Other authors discussed different iterative approaches, which alternate between a LP model and a simulation model (Hung and Leachman 1996; Byrne and Bakir 1999; Kim and Kim 2001). A LP model determines a production plan based on (initial) estimated lead times. A detailed simulation model of the production facility returns the realized lead times for this production plan. The new lead times are then input into the LP model to determine a new production plan. These procedures iterates until a convergence criterion is satisfied. An analysis of two different iterative approaches is given in (Irdem et al. 2010) and a comprehensive overview of these different approaches and methods can be found in (Pahl et al. 2007; Missbauer and Uzsoy 2010).

In many recent studies the uncertainty, especially of the demand, is focused. The usual approach in the industry is the calculation of safety stocks using methods of the inventory management. The replenishment lead times are approximated by statistical distribution, and the relationship between the workload and the lead times are ignored. The extension to the queuing theory was considered by (Buzacott and Shanthikumar 1993; Rao et al 1998; Hopp and Spearman 2001). The CF approach is quite comparable.

In research, robust planning is also analyzed as stochastic or robust optimization as proposed by (Escudero et al. 1993; Mulvey and Vanderbei 1995; Scholl 2001). One major disadvantage, especially in an industrial environment, is the run time of stochastic optimization models. Most of these models regard demand as uncertain, lead times are usually assumed as being constant.

(Ravindran et al 2011) proposed a production planning model for a single-stage single-product system that integrates release planning and safety stock considerations. Due to the stochastic nature of the demand, chance constraints are used to plan inventories

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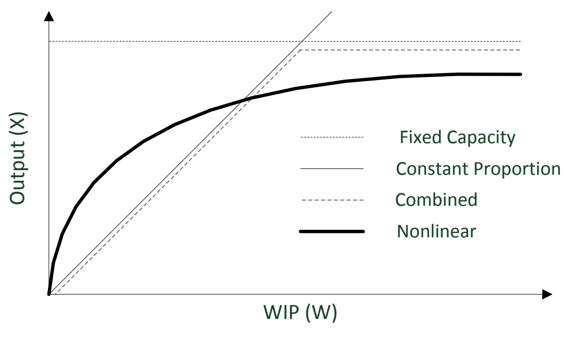
to achieve the desired service levels. In our research we extended this model to the consideration of multiple products, as well as for the use in a rolling planning environment. To capture the nonlinear relationship between the resource utilization and the lead times, a nonlinear CF is used to represent the capacity constraint. The next section gives an overview of the Clearing Function concept. Then we introduce our test problem and show how a CF can be estimated. Then the LP-Model as well as the experimental environment will be described. At the end the research results are discussed and future research directions are shown.

PREVIOUS RELATED WORK

Several authors (Karmarkar 1989; Missbauer 2002; Asmundsson et al. 2006, 2009; Ravindran et al. 2011; Kacar et al. 2012) represent the behavior of the relationship between the workload and the output of a capacitated production resources by using nonlinear CFs. Figures 1, based on (Karmarkar 1989), depicts several CFs considered in the literature up to date. The CF "Fixed Capacity" describes a fixed output over the period, regardless of the WIP inventory in the production system or at the resource. The CF "Constant Proportion" by (Graves 1986) characterizes an unlimited linear output at increasing WIP inventories. As a result, it is assumed that the production system, regardless of the workload, have a fix lead time and an infinite amount of output is possible. The CF "Combined" improves the "Constant Proportion", by limiting the maximum amount of output by an upper bound and is described in (Hopp and Spearman 2001). Most LP models avoid a nonlinear capacity constraint by using a linear relation like the CF "Combined". Just the CF "Nonlinear" proposed by (Srinivasan et al. 1988; Karmarkar 1989) takes into account the nonlinear relationship between the workload and the expected output of a capacitated resource or production system.



Figures 1: Examples of Clearing Functions (Karmarkar 1989)

To estimate a CF it is a common approach to derive them using steady-state queuing analysis. A CF determines the expected or maximum output of a capacitated resource over a given period of time as a function of some measure of the work in process (WIP) inventory (Missbauer and Uzsoy 2010). In (Asmundsson et al. 2009) the expected WIP for a G|G|1 queuing system in steady state is given as:

$$W = \frac{\left(c_a^2 + c_s^2\right)}{2} \cdot \frac{p^2}{\left(1-p\right)} + p$$

where p denote the utilization of the server and c_a and c_s the coefficients of variation of the service and interarrival times. Solving this equation for p we obtain:

$$p = \frac{\sqrt{\left(W+1\right)^2 + 4W\left(c-1\right)} - \left(W+1\right)}{2\left(c-1\right)}$$

where

$$c = \frac{\left(c_a^2 + c_s^2\right)}{2}$$

(Asmundsson et al. 2009) suggested using the utilization p as a surrogate for the output to obtain the CF which has the desired concave form. For a fixed c value the output increase with a higher WIP inventory (W) at a declining rate. A different approach, suggested by (Missbauer and Uzsoy 2010), derive the CF using a M|G|1 queuing system in steady state. Hence the average throughput E(X) is related to the expected WIP level E(W) as follows:

$$E\left(X\right) = C \cdot \frac{E\left(W\right)}{E\left(W\right)+k} \quad \text{where} \quad k = \frac{\mu\sigma^2}{2} + \frac{1}{2\mu}$$

Here C denotes the maximum capacity per period of the resource and μ, σ the mean and variance of the processing time distribution.

Due to the high complexity and the existing interdependencies, it is not readily possible to build and solve queuing models for real existing production systems. For this reason (Asmundsson et al.2006, 2009; Kacar and Uzsoy 2010; Kacar et al. 2012) suggested an empirical approach to estimate clearing functions. They use in their research a simulation model of a scaled-down semiconductor wafer fabrication facility, studied by their research group (Kayton et al. 1997). The processing time for each workstation is characterized by a statistical distribution and all products are subject to the same processing time distribution at each station. To estimate the CF for this production system, (Asmundsson et al. 2006) generate five randomly demand realizations and develop corresponding release schedules by using the fixed lead-time LP model developed by (Hackman and Leachman 1989) and a planning horizon of 70 periods. For each release schedule and 50 different simulation replications (m=50) the observations of throughput ($x_{t,s}$) and average

WIP ($w_{t,s}$) for Period t and simulation run s were collected. The expected WIP ($E(W_t)$) and the corresponding expected output ($E(X_t)$) for each period t are estimated as follows:

$$E\left(W_t\right) = \frac{1}{m}\sum_{s=1}^{m} w_{t,s} \quad \wedge \quad E\left(X_t\right) = \frac{1}{m}\sum_{s=1}^{m} x_{t,s}$$

The CF can be estimated by visually fit a CF through the collected data points (Asmundsson 2006).

TEST PROBLEM

We consider a single-level multi-product production system. The demand in each period is independently and normally distributed and the ratio of demand for all products is identical. Our simulation model contains 5 workstation (resources) and 8 products. An overview of our model is given in Table 1.

Table 1: Process chart for the products.

Product	Resource	Setup time [seconds]	Process time [seconds]
Part01	Cutting Turning Milling Grinding	20 50 50 30	40 100 100 50
Part02	Turning Milling Cleaning Grinding	50 50 30 30	150 100 100 80
Part03	Milling Cleaning Grinding	60 30 30	90 80 100
Part04	Turning Grinding	50 30	30 30
Part05	Cutting Turning Milling Grinding	20 50 50 30	40 100 100 50
Part06	Turning Milling Cleaning Grinding	50 50 30 30	150 100 100 80
Part07	Milling Cleaning Grinding	60 30 30	90 80 100
Part08	Turning Grinding	50 30	30 30

In contrast to the approaches of (Asmundsson et al. 2006, 2009; Kacar and Uzsoy 2010; Ravnindran et al. 2011; Kacar et al. 2012) in our research we assume deterministic process times.

DETERMINE CLEARING FUNCTIONS

Per simulation we determine the behavior of the capacitated production system under different workload situations. We assume a constant WIP inventory for all products k over the entire simulation horizon. This desired target WIP inventory is for all products k equal and is set from 1 to 350 pieces. The upper limit was determined as the maximum output of the production system was reached and a higher WIP inventory does not lead to a higher output. To gain statistically significant data the simulation horizon of each run is set to 1000 periods, verified by our tool which analyzes the deviation of the figures.

For each product k we estimate a CF by collecting the output data ($X_{k,t}$) of a product k in a period t over the entire simulation horizon. Due to the mutual interferences of the other products which are released, different WIP constellations can be achieved. At the beginning of a period t the release quantity for each product k is to determine that the desired target WIP inventory is reached. The WIP inventory is represented by the workload which is defined by the quantity released at the beginning of a period t multiplied by the cumulative processing times tb_k. This cumulative processing time is calculated by the sum of all operations o, which must be accomplished for a product k ($o \in O_k$). With $\hat{W}_{k,t}$ denoting the WIP inventory measured in units of time at the end of period t for product k the workload at the end of a period t is defined by the released quantity $R_{k,t}$ multiplied with the cumulative processing times less the units of work which are already processed and defined by $\lambda_{k,t}$.

$$\hat{W}_{k,t} = R_{k,t} \cdot \sum_{o \in O_k} tb_{k,o} - \lambda_{k,t}$$

Hence the release quantity $R_{k,t}$ to achieve the desired target WIP $W_{k,\text{Target}}$ is defined by:

$$R_{k,t} = W_{k,\text{Target}} - \frac{\hat{W}_{k,t-1}}{\sum_{o \in O_k} tb_{k,o}}$$

The output values ($X_{k,t}$) of finished goods for each product k and period t are collected and the average output for a product k over all periods t is calculated. In total 350 simulation runs were performed and the target WIP was the same height for all 8 products and was increased simultaneously. For each product k we obtain a CF which defines the expected output for a WIP inventory from 0 to 350 pieces. This leads to an approximation to the average behavior of the capacitated system and the expected output of a product k depending on the WIP inventory of the product k.

MP-DYNIP-B MODEL

We now introduce the production planning model. This model is based on the “dynamic inventory position” (DYNIP) model of (Ravindran et al. 2011). An overview of this model can be found in (Ravindran et al. 2011; Herrmann and Lange 2013). For our research we extended the model to the consideration of multiple products, as well as for the use in a rolling planning environment. The notation used in the formulation is given below (the expected value of a variable x is described by E(x)).

Parameter:

- $\alpha_{k,RLT}$: Service level for product k in the replenishment lead time
- $E(D_t)$: Mean of the normally distributed demand of product k in period t.
- $G_{k,[t,t+L_t]}$: Distribution Function (CDF) of the cumulative demand from period t to period t + Lt.
- h_k : Unit inventory holding cost for product k.
- $L_{k,t}$: Lead time for product k in period t.

Decision variables:

- $B_{k,t}$: Backorders for product k in period t. Initial backorders at the start of period 1 will be denoted by $B_{k,0}$.
- $I_{k,t}$: Inventory at the end of period t for product k. Initial inventory at the start of period 1 will be denoted by $I_{k,0}$.
- $R_{k,t}$: Release quantity of product k, released into the system at the beginning of period t.
- $X_{k,t}$: Production quantity (output) of product k available at the beginning of period t.
- $W_{k,t}$: WIP inventory from product k at the end of period t.
- $Y_{k,t}$: Change in planned inventory position of product k in period t.

Objective Function

$$Z = \sum_{k=1}^{K}\sum_{t=1}^{T}\left(h_k \cdot \left(E\left(I_{k,t}\right)+E\left(W_{k,t}\right)\right)\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{1}$$

Subject to

$$E\left(I_{k,t}\right) = \left(I_{k,0}-B_{k,0}\right)+\sum_{i=1}^{t}E\left(X_{k,i}\right)-\sum_{i=1}^{t}E\left(D_{k,i}\right) + \sum_{i=1}^{t}E\left(B_{k,i}\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{2}$$

$$E\left(W_{k,t}\right) = W_{k,0}+\sum_{i=1}^{t}\left(Y_{k,i}+E\left(D_{k,i}\right)-E\left(X_{k,i}\right)\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{3}$$

$$\left(\left(I_{k,0}-B_{k,0}\right)+W_{k,0}\right)+\sum_{i=1}^{t}Y_{k,i} \ge G^{-1}_{k,[t+1,t+L_t]}\left(\alpha_{k,RLD}\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{4}$$

$$E\left(X_{k,t}\right) \le CF_k\left(W_{k,t-1}\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{5}$$

$$Y_{k,t}+D_{k,\min} \ge 0 \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{6}$$

$$E\left(I_{k,t}\right),E\left(W_{k,t}\right),E\left(X_{k,t}\right),E\left(B_{k,t}\right) \ge 0 \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K \tag{7}$$

The objective function (1) minimizes the sum of the total costs of finished goods and WIP inventory for all products k and periods t. The inventory balance equation (2) determines the inventory of finished goods at the end of a period t. The right side of this equation must not be negative, since this would wrongly reduce the value of the objective function. Considering a situation where the expected output is lower than the expected demand these quantities have to be produced in previous periods. Hence the output quantity is limited by the capacity constraint (5) this is not always possible. Therefore the backorders $B_{k,t}$ have been integrated into the equation. An integration of the backorders into the objective function is not required as the service level restriction (4) regulate the amount of backorders. Since the model is used in a rolling planning environment backorders can exist at the beginning of a planning run. These backorders at the beginning of a planning run must be taken into account as in equation (2) and (4) done by $B_{k,0}$. Thus the model of (Ravindarn et al. 2011) is in addition to the consideration of multi products, extend by the consideration of backorders to enable the use in a rolling planning environment. The WIP inventory at the end of a period t is determined by the amount of the release quantity and the output of finished goods at the beginning of this period t which is described by the WIP balance constraint (3). We assume a minimum lead time of 1 period to create a consistency to the inventory management. Hence the release quantities, which are released into the production system at the beginning of period t, are at the earliest in the beginning of period t+1 available. To meet the desired service level the demand during the replenishment lead time must be covered by the available stock, determined by the reorder point. This is expressed by the service level constraint (4). The corresponding value of the distribution function for a specific service level is to determine. This can be computed through approximation functions or stochastic tables. Referred to (Herrmann 2011) the service level constraint for a normal distributed demand can be transformed. Hence this leads to the transformed service level constraint given below:

$$\left(\left(I_{k,0}-B_{k,0}\right)+W_{k,0}\right)+\sum_{i=1}^{t}Y_{k,i} \ge L_{k,t}\cdot E\left(D_{k,t}\right) + \sqrt{L_{k,t}}\cdot\sigma_{k,t}\cdot\Phi^{-1}_{N(0,1)}\left(\alpha_{k,RLD}\right) \quad \forall 1 \le t \le T \wedge \forall 1 \le k \le K$$

The capacity constraint (5) is represented by a clearing function for each product which represents the behavior of the capacitated production system. Depending on the WIP inventory of a product k in the production system, the production quantity (output) is limited. Equation (6) prevent the case, that the release quantity may be negative, where D_{min} is a lower bound on the value of demand in any period. The non-negativity constraints are given by equation (7). It is important to note, that two different lead times are consider within the model. The replenishment lead time in the service level constraint (4) is an exogenous parameter required to approximately achieve the desired service levels. In our experiments the replenishment lead time $L_{k,t}$ is set to 1. The other lead time is the time between work released into the system and becoming available as finished goods, represented by the CF in the capacity constraint (5).

This optimization model determine the required changes of the inventory position represented by $Y_{k,t}$ for each product k and period t. The release quantity $R_{k,t}$ is determined by these auxiliary variable $Y_{k,t}$ and the actual demand $D_{k,t}$, which is described by the equation below.

$$R_{k,t} = Y_{k,t} + D_{k,t} \qquad \forall 1 \le t \le T \wedge \forall 1 \le k \le K$$

EXPERIMENTAL DESIGN

In simulation studies we compared the performance of our MP-DYNIP-B model with two base stock inventory policies. For this purpose two performance measures were chosen, the mean value and standard deviation of the stock and the reached service level. In this section we specify the generation of the demand scenarios and introduce the base stock inventory policy used for comparison.

Demand Realization

The uncertainty of the demand is represented by a variation of the mean values and standard deviation of the demand quantities over the time. The coefficient of variation of the demand distribution is assumed to be constant and is set to 0.3. Thus the variances can be different since the means are different in each period. According to (Ravindran et al. 2011) we generate the demand means via two control variables. To specify the number of periods between changes of the mean, the value Δ_n ($1 \le n \le N$) will be introduced. The value N is defined by the required number of mean changes to reach the simulation horizon. This value Δ_n is determined by using a uniform distribution with the lower bound $\delta_{\min}$ and upper bound $\delta_{\max}$. The new mean value μ_n ($1 \le n \le N$) for the next Δ_n periods is also determined using a uniform distribution with a specified lower bound $\rho_{\min}$ and upper bound $\rho_{\max}$. By using these control variables we obtain different mean values for the entire simulation horizon. We generated three different demand conditions referred as scenario I (S-I), scenario II (S-II) and scenario III (S-III) by using different parameter for $\rho_{\min}$ and $\rho_{\max}$. In S-I we determined the values for the new mean demand by $\mu_n = U(70,80)$, in S-II we used $\mu_n = U(60,90)$ and in S-III the values $\mu_n = U(50,100)$ were chosen. For all three scenarios the number of periods between the changes of the demand means was determined by $\Delta_n = U(3,12)$. These scenarios specify different situations of the demand uncertainties.

Comparison Model

We compare the performance of our MP-DYNIP-B model with two base stock inventory policies. Firstly we consider a dynamic order quantity q, which depends on the actual demand of a period t ($q_t = D_t$). The reorder point s is defined as

$$s_k = L_k \cdot \mu_k + \sqrt{L_k} \cdot \sigma_k \cdot \Phi^{-1}_{N(0,1)}\left(\alpha_{k,RLD}\right)$$

where μ_k and σ_k denotes the average and the standard deviation of the demands over the simulation horizon. This model is referred as Basestock-Policy. Secondly we assume a (s, q)-Policy with a constant order quantity of 120 pieces (q=120). To determine the reorder point s we consider the so-called undershoot (U), which is defined as the difference between the reorder point s and the inventory position at the moment immediately before a replenishment order is released. A detailed description of the determination of the mean E(U) and variance Var(U) of the undershoot for a normal distributed demand can be found in (Herrmann 2011). Hence the mean and variance of the demand during the replenishment lead time is defined by the equation shown below.

$$E\left(Y_k^*\right) = \mu_k + E\left(U\right) \wedge \; Var\left(Y_k^*\right) = \sigma_k^2 + Var\left(U\right)$$

Thus, the reorder point s_k for a product k can be determined by the following equation.

$$s_k = L_k \cdot E\left(Y_k^*\right) + \sqrt{L_k} \cdot Var\left(Y_k^*\right) \cdot \Phi^{-1}_{N(0,1)}\left(\alpha_{k,RLD}\right)$$

The replenishment lead time L_k for product k is for both inventory policies set to 1 period.

EXPERIMENTAL RESULTS

To gain statistical significant figures a simulation horizon of 1000 periods was defined and verified by our tool. As performance measures we compare the average (AVG) and the standard deviation (SD) of the inventory position and the reached service level over all products k and periods t. In table 3 the results for a target service level of 90% are shown.

Table 3: Experimental results of all models and scenarios for a target service level of 90%.

Target Service level = 90%					
Model	Service Level		Inventory Position		Scenario
	AVG	SD	AVG	SD	
Basestock	88.1	2.9	39.7	28.2	S – I
(s, q) – Policy	88.9	1.2	77.7	41.0	S – I
MP-DYNIP-B	90.8	0.8	40.2	28.0	S – I
Basestock	85.5	3.7	42.6	29.5	S – II
(s, q) – Policy	87.3	1.0	81.4	42.2	S – II
MP-DYNIP-B	90.4	1.0	42.9	28.8	S – II
Basestock	85.8	2.3	48.7	30.3	S – III
(s, q) – Policy	84.4	2.1	88.0	45.4	S – III
MP-DYNIP-B	89.6	1.3	45.8	30.3	S – III

For all scenarios the MP-DYNIP-B model nearly reached the desired service level of 90%. In scenario I and II the Basestock-Policy gain lower service levels as the (s, q)-Policy, in scenario III the Basestock-Policy gain a better service level. For all scenarios the average inventory position of the (s, q)-Policy is almost twice as high as in the other models. This is due to the high reorder point, which consider the undershoot, to capture the uncertainty of the demand. The Basestock-Policy performs better, because of the dynamic of the order quantity, depending on the actual demand. The MP-DYNIP-B model determines the capacity better and considers the relationship between the WIP inventory and the output quantity accurate. Table 4 contains the experimental results for a target service level of 95%. These results are similar to the results shown in table 2.

Table 4: Experimental results of all models and scenarios for a target service level of 95%.

Target Service level = 95%					
Model	Service Level		Inventory Position		Scenario
	AVG	SD	AVG	SD	
Basestock	92.8	1.9	42.0	26.3	S – I
(s, q) – Policy	93.8	1.0	87.7	43.3	S – I
MP-DYNIP-B	95.0	0.7	43.7	25.8	S – I
Basestock	91.8	1.6	45.8	27.4	S – II
(s, q) – Policy	92.1	1.4	91.4	44.6	S – II
MP-DYNIP-B	94.9	1.5	46.5	26.9	S – II
Basestock	91.3	1.9	52.1	29.2	S – III
(s, q) – Policy	90.0	1.7	98.7	48.4	S – III
MP-DYNIP-B	93.4	2.2	49.8	28.7	S – III

SUMMARY AND FUTURE DIRECTION

Our research show, how a CF specific to a product k for a capacitated production system, using deterministic process times and multiple products, can be estimated. We extend the model of (Ravindran et al. 2011) to consider multiple products and integrate backorders for the use in a rolling planning environment. The simulation experiments indicate that the MP-DYNIP-B model outperforms the inventory management policies used in this research.

In future studies further insights of the performance of our model may be provided by using different replenishment lead time values and inventory policies. The extension of the model to the consideration of a bill of material as well as the estimation of a CF for such a model is task for further research. Also an extension to the approaches of the stochastic optimization and the consideration of multiple demand scenarios to gain robust planning results should be in the focus of interest.

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