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# COMPARING THE PERFORMANCE OF TWO DIFFERENT CUSTOMER ORDER BEHAVIORS WITHIN THE HIERARCHICAL PRODUCTION PLANNING

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## ABSTRACT

A hierarchical production planning structure enables manufacturing systems to handle customer disturbances with different measures on different planning levels. Two different kinds of customer order behavior can be observed and are as well discussed in literature. In the first, being forecast-evolution-behavior, customers provide a forecast quantity for a specific due date for a long horizon in advance and update their forecast quantities periodically. In the second, being customer-required-lead-time-behavior, customers demand stochastic order amounts with a customer-required-lead-time whereby the manufacturing company generates an aggregated forecast, e.g. for product groups. These required lead times are usually shorter than the forecast-evolution-horizon, but order quantities do not further change. For comparing the influence of both order behaviors on a hierarchical production planning system, a simulation study is performed in which logistic performance measures such as service-level, utilization, capacity-, inventory- and tardiness-costs are analyzed with respect to a normalized forecast quality measure.

## 1 INTRODUCTION

Two different kinds of how customers provide information about the required demand to their suppliers can be observed and are as well discussed in literature. Firstly, this is the forecast evolution behavior (FEV) where customers provide a forecast quantity for a specific due date for a long horizon in advance and update their forecast quantities periodically. At each update occurrence, the customer changes its quantity or due date. Usually, less information on customer orders is available for time periods further in the future. Secondly, when the customer required lead time behavior (CRL) applies the manufacturing company generates an aggregated forecast for a long time in advance (e.g. planned order amount per month and product group), sometimes in cooperation with their customers. The customers then order a stochastic order amount with a stochastic required lead time. In both order behaviors manufacturing companies are facing the problem of information dynamics and uncertainty, i.e. stochastic behavior of arrivals, due dates and order amounts over time. However, hierarchical production planning (HPP) models such as the MRP II (manufacturing resource planning) concept are mitigating the negative effects of this problem. MRP II 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 production planning (APP). The APP 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 APP optimization problem.

The main functions of intermediate 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 Orlicky 1975 for MRP). Short-term control conducts scheduling and dispatching tasks for production orders and available resources.

Based on the decision hierarchy in manufacturing and the information uncertainties, there is still a research gap concerning the influence of information dynamics and uncertainties on the decisions taken on the upper hierarchical level. Ignoring this information uncertainty influence leads to a lack of coordination and integration also reported in surveys by Fleischmann and Meyr (2003), Kok and Fransoo (2003) and Missbauer and Uzsoy (2011).

A considerable amount of literature is available on aspects of the problem of information uncertainty such as stochastic demand, customer required lead time and forecast errors and their influence on the two intermediate planning components MPS and MRP. In this literature stream, planning parameters including periodicity, safety stocks, planned lead-times and lot sizes are optimized with respect to logistic performance measures like a service level threshold value or overall costs divided into capacity, tardiness and inventory costs. Furthermore, some literature discusses the interaction of different planning levels in a hierarchical production planning structure. To solve the above mentioned problems, analytic models, simulation, heuristic techniques or decomposition approaches are used.

As noted above in the forecast evolution models less information on customer orders is available for time periods further in future. The future demand forecasts appear a certain time in advance and gradually change until the realization of the order at its due date. In this model, demands have a higher variance the longer their time to due date is. Heath and Jackson (1994) modeled the evolution of forecasts as an extension of the Martingale Model for Forecast Evolution (MMFE) which is a way for modeling the evolution of forecasts (Hausman 1969). They analyzed safety stock levels for a multi-product / multi-plant production conducting a simulation study. Güllü (1996) explores how total system costs and inventory positions are affected when forecasts are incorporated explicitly in production / inventory systems. He assumes that forecasts for demand of a certain item are available in each period, and they evolve from one period to the next applying an additive evolution model. In order to analyze the effects of the forecasts on the production/inventory system he compares the optimal ordering policy and the expected costs of the model that keeps forecasts with that of a comparable standard inventory model. The paper shows that under mild assumptions the new model yields lower expected costs and inventory levels than the standard model. Baykal-Gürsoy and Erkip (2010) review inventory planning approaches in order to find out demand-forecasting requirements. The authors consider single- and multi-item supply chains under stationary and nonstationary, correlated demand. In their study they also use the MMFE-model.

One of the first articles which consider the possibility that some information about the customer demand in advance of the respective demand can be used in MTS production systems is written by Buzacott and Shanthikumar (1994). In this paper the difference between safety stock and safety time within an MTS inventory replenishment system is discussed. It is found that safety time is preferable to safety stock if there is a good forecast, i.e., the customer required orders and their due dates are known for a long period in advance. The safety time considered in this paper is defined as planned lead time minus average production lead time. This concept presented in Buzacott and Shanthikumar (1994) for safety time is equivalent to applying a planned lead time in a MTO system but additionally a safety stock is held. Hariharan and Zipkin (1995) discuss the influence of customer required lead time for a single-stage and multi-stage MTS production system. They test different reorder policies and find that in their model a constant customer required lead time leads to the same result as a respective reduction of supply lead time. This concept of knowing the demand in advance even in stock replenishment systems working under MTS is the basis for the literature stream on advance demand information. In this stream of literature either the optimal replenishment strategy or the optimal parameters of a predefined replenishment strategy are optimized usually assuming a constant customer required lead time. Karaesmen et al. (2002) for example analyze a discrete time single-stage MTS production system with customer demand known a constant period in advance. For a base stock policy the parameters order release time, which is equivalent to planned lead time, and base stock level are optimized based on inventory and backorder costs. Some recent papers using advanced demand information as a stochastic or deterministic customer required lead time are Karaesmen et al. (2004), Liberopoulos (2008), Wijngaard (2004), Wijngaard and Karaesmen (2007), Tan et al. (2007), and Gayon et al. (2009).

The MRP II planning components MPS and MRP outweigh a part of the information dynamics and uncertainty that the production system is dealing with. In the current study this effect is investigated for the two different order behaviors FEV and CRL. For the two possibilities how customers provide information to their suppliers 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 further conducts MPS, MRP and dispatching functionalities. For the FEV behavior forecast error is random. For the CRL behavior the monthly forecast error and the order amount are random. To compare the performance of the two order behaviors within the MRP II structure a forecast quality measure is developed. For different levels of forecast quality of the CRL and FEV order behavior, a numerical study is conducted where the amount of capacity flexibility needed (1- $\eta$) in the APP (MIP-model) to reach an appropriate service level is investigated with respect to minimal overall costs including capacity, tardiness and inventory costs. In detail it is observed how the optimal planned utilization factor $\eta_{opt}$ changes when the forecast quality decreases. Especially the performance difference of the two investigated order behaviors within the hierarchical production planning environment is analyzed.

This article extends the literature on hierarchical production planning by investigating the influence of long term decisions on the key performance indicators of the stochastic production system for two different order behaviors. A similar study comparing the two order behaviors within a HPP-environment has not been performed and published yet. Therefore a discrete event simulation model which mimics the HPP-structure is extended by the two order behaviors CRL and FEV. For our research discrete event simulation is identified as an appropriate solution method due to the fact that it is not possible to analytically model the whole MRP II structure with its links between the planning steps on different planning levels and the two stochastic customer order behaviors. To make these behaviors comparable at all a normalized forecast quality measure is introduced. In a simulation study different demand levels and cost rates are investigated. The remainder of this article is structured as follows. After the model description in Section 2 explaining the used HPP-framework with the embedded APP model, the investigated problem structure and parameters are presented in Section 3. Section 4 reports the results of the numerical study and conclusions are provided in Section 5.

## 2 MODEL DESCRIPTION

The hierarchical production planning approach as illustrated in Figure 1 is modeled with a simulation generator (Hübl et al. 2011; Felberbauer, Altendorfer and Huebl 2012). The previous published simulation generator is extended by modeling the FEV and CRL order behaviors within the discrete event simulation model. Rolling horizon planning is conducted for the long and intermediate range planning level. For the APP an interface between the simulation software AnyLogic© and the standard MIP-solver CPLEX© is built. The APP is executed three times per year for a planning horizon T of twelve months and the results are used within the simulation model for the mid- and short term planning. Due to rolling horizon planning, only the plan for the next four months is used during simulation and therefore the problem of zero inventory at the end of the planning horizon T can be ignored. The calculation of the optimal production program is a function call within the simulation model and there is a cross data exchange between the simulation model and the MIP-solver. The MIP-solver uses transaction data (inventory levels) and master data (forecasts, processing times and shift system possibilities) from the simulation model and returns the optimal production program (production amount, respective inventory levels and internal / external capacity levels).

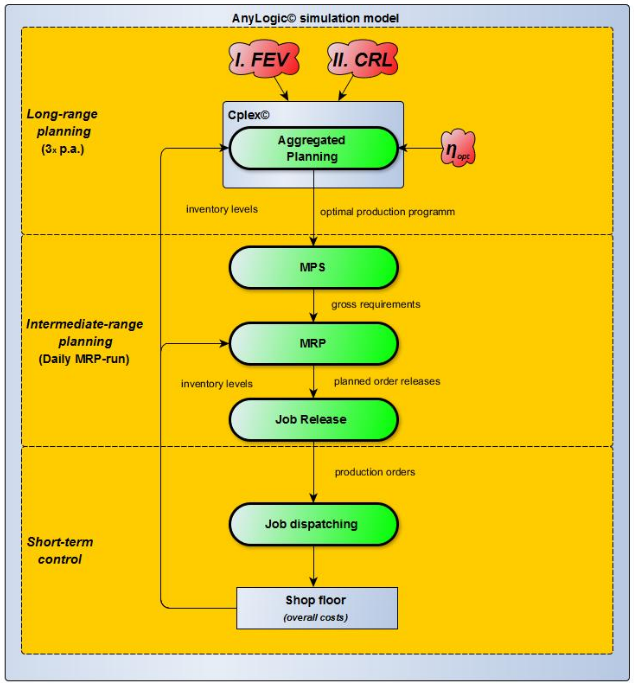


Figure 1: Hierarchical Production Planning approach

The intermediate-range planning uses the disaggregated optimal production plan and actual customer orders in the MPS for the calculation of the gross requirements according to the cumulative MPS method. In the daily MRP run, planned order releases are calculated with the main MRP-functions netting, lot sizing, backward scheduling and bill of material (BOM) explosion. In the job release module planned orders from the MRP run are converted to real production orders if all required sub materials are available. Finally, the production orders are produced on the shop floor according to the routing information and dispatching rule. The available capacity of the shop floor is determined by the applied shift system and the external capacity hired according to the optimal production program. The shop floor performance is measured in overall costs consisting of internal and external capacity costs, inventory costs and tardiness costs.

The APP is modeled as a MIP by employing the decision variables $x_{p,t}$, $e_{t,j}$, and $w_{t,j,s}$. $x_{p,t} \geq 0$ is the optimal production program of sales product $p$ out of $P$ sales products in time period $t$ (month). $e_{t,j} \geq 0$ is the capacity of machine $j$ in time period $t$ which is processed by an external company which is able to provide the required technology of machine $j$ out of $J$ machines. Finally, the binary decision variables $w_{t,j,s} \in \{0,1\}$ are introduced for setting the applied work schedule and therefore the available internal capacity per machine $j$ and time period $t$. The optimal production program $x_{p,t}$ and the respective inventory levels $l_{p,t}$ are disaggregated from months $t$ into days $\tau$. The disaggregated inventory levels are used in the MRP-Planning approach (mid-term planning) of the simulation, which is calculated daily. The optimal production program $x_{p,t}$ is used as input for the MPS. In our model, the Gregorian calendar of 2013 is used and two shift plan models (five days per week with two shifts; five days per week with three shifts) are available. The internal capacity per machine $j$, month $t$, and shift plan $s \in \{1,2\}$, $K_{t,j,s}$ relies on the respective shift plan and the calendar of the considered year. For the two / three shift model and a month $t$ with 20 working days the internal available capacity $K_{t,j,1} = 320$ and $K_{t,j,2} = 480$ hours respectively. The following MIP problem is solved:

$$\sum_{t=1}^{T}\sum_{j=1}^{J}\left(e_{t,j}c^{e} + \sum_{s=1}^{2} K_{t,j,s}c^{i}\, w_{t,j,s}\right) + \sum_{p=1}^{P} c^{h}\, l_{p,t} \rightarrow \min_{x_{p,t}\ w_{t,j,s}\ e_{t,j}} \tag{1}$$

subject to

$$\sum_{s=1}^{2} w_{t,j,s} = 1 \qquad t = 1,\dots,T \quad j = 1,\dots,J \tag{2}$$

$$\sum_{p=1}^{P} x_{p,t}a_{p,j} \leq \eta \sum_{s=1}^{2} K_{t,j,s}w_{t,j,s} + e_{t,j} \qquad t = 1,\dots,T \quad j = 1,\dots,J \tag{3}$$

$$l_{p,t} = l_{p,t-1} + x_{p,t} - F_{p,t} \qquad p = 1,\dots,P \quad t = 1,\dots,T \tag{4}$$

$$l_{p,t}, x_{p,t} \geq 0 \qquad p = 1,\dots,P \quad t = 1,\dots,T \tag{5}$$

$$e_{t,j} \geq 0 \qquad t = 1,\dots,T \quad j = 1,\dots,J \tag{6}$$

$$w_{t,j,s} \in \{0,1\} \qquad t = 1,\dots,T \quad j = 1,\dots,J \quad s = 1,\dots,2 \tag{7}$$

The objective function (1) minimizes the costs of internal / external capacity (at cost rate $c^i$ and $c^e$ for machine *j* respectively) and the inventory costs (inventory cost rate per day $c^h$) which accrue by fulfilling the required demand. The main trade-off treated in the APP problem is between pre-production on stock and application of additional internal or external capacity. Due to constraint (2) only one shift plan can be applied for one machine per time period *t*. Constraints (3) ensure that the capacity needed to produce the optimal production program on the machines is lower than or equal to the available capacity of internal and external resources. The required capacity with respect to time period *t* and machine *j* is calculated using the processing time $a_{p,j}$ per sales product *p* and machine *j* and the respective optimal production program $x_{p,t}$. The external capacity is unlimited and the internal available capacity per machine is dependent on the applied shift plan and the planned utilization factor $\eta$. The planned utilization factor is a real number between zero and one and defines the planned internal production system utilization. $\eta$ provides excess capacity in the internal production system which is necessary to react to the stochastic behavior of the demand fluctuation and the forecast error. At the call of the APP, the actual inventories of the simulation for all sales products are defined as start inventories $l_{p,0}$. Constraints (4) ensure that for the planning horizon *T* the required demand $F_{p,t}$ per period *t* is fulfilled by the optimal production program and inventory. Finally, the constraints' (5)-(7) define the decision variables. Two important points to mention are that the MIP-problem always stays feasible due to the unlimited external capacity and therefore no tardiness costs are included in the objective function of the APP. In the real production system with stochastic influences, however, tardiness costs will also occur, which are balanced in the following against the additional costs caused by the planned utilization factor $\eta$. Note that a lower $\eta$ leads to higher optimal costs in the MIP problem but in the real stochastic production system modeled with this decreased $\eta$ leads to lower tardiness costs since additional capacity is available to react to stochastic influences.

# 3 PROBLEM DESCRIPTION

The modeled production system follows a flow shop structure inspired by different production facilities operating in the automotive sector. The production system consists of six machines (M1-M6).

Figure 2a shows the BOM and the low level code (LLC) for the four items and six materials. All items as well as materials in LLC 0 to LLC 2 are MRP planned. LLC 0 contains all sales products $p$ (items). 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. In this study purchased parts are always available and need not be taken into consideration for the planning.

a. b.

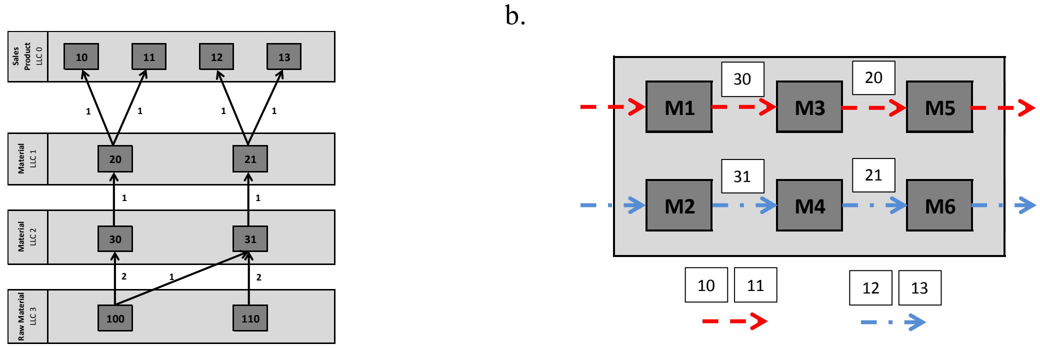


Figure 2: Bill of material and routing information

Figure 2b shows the material flow of the items. Items 1x are produced on machine M5 or M6, items 2x are produced on M3 or M4 and items 3x are produced on M1 or M2. Generally, the production orders generated by the MRP-planning algorithm are sorted by the modified earliest due date (MEDD) dispatching rule where the production orders are sorted according to the due date of their parent item (Panwalkar and Iskander 1977). Each processing step requires a deterministic processing time which differs according to the low, medium and high capacity demand scenarios. Within one scenario the processing time is equal for all items / materials and machine-routing-combinations.

The overall forecast amount $F_p$ per year and sales product is a deterministic value and is equal for all investigated scenarios. The forecast per sales product and month is constant and is calculated according to (8). Note that $T$ is the number of months in a year, thus 12. For all capacity demand scenarios the overall forecast amount $F_p$ of sales products 10 and 12 are 12,000 pieces for each and 18,000 pieces for sales products 11 and 13 respectively.

$$F_{p,t} = \frac{F_p}{T} \tag{8}$$

***CRL order behavior***

For the CRL behavior the forecast error incorporates the stochastic difference between monthly demand from forecast (being deterministic, see equation (8)) and the stochastic realized monthly demand. The forecast error $\varepsilon_{p,t}$ is an identically independent truncated-normal-distributed random variable with an expected value $E[\varepsilon_{p,t}] = 0$ and variance $Var[\varepsilon_{p,t}] = (\alpha F_{p,t})^2$. The forecast error parameter $\alpha$ defines the quality of the forecast and is independent of time period $t$ and item $p$. The random monthly demand per sales product $p$ and time period $t$ is defined as $D_{p,t} = F_{p,t} + \varepsilon_{p,t}$.

The actual amount per order $O_p$ for item $p$ is log-normally distributed with expected value $E[O_p] = 33$ and variance $Var[O_p] = 24.5$ for sales products 10 and 12, as well as expected value $E[O_p] = 49$ and variance $Var[O_p] = 54.02$ for items 11 and 13 which leads to a coefficient of variation of 0.15 for all items. The arrival rate $\lambda_{p,t}$ with respect to item $p$ and time period $t$ is calculated according to $\lambda_{p,t} =$

$\frac{D_{p,t}}{E[O_p]} = \frac{F_{p,t}+\varepsilon_{p,t}}{E[O_p]}$. Note that in the simulation study the order rate $\lambda_{p,t}$ is adjusted to account for the forecast error but the order amounts remain stable. Each customer order requests a deterministic customer required lead time $L = 3$ . Figure 3 illustrates the order behavior of one single customer order for item $p$ within the planning system. Figure 3 shows that 20 days before delivery (dependent on the chosen MRP-planning horizon, the order release itself is dependent on the sum of lead times of superior materials) there is only the forecast information on the expected customer demand with a certain due date available. The 33 pieces are a forecast value derived according to the monthly forecast amount $F_{p,t}$ (e.g. 1000 pcs.) and the amount of days per month (e.g. 30 days). This information stays unchanged until the real customer order arrives 3 days in advance. At this point in time the customer provides information about the real customer order amount. Dependent on the low level code and the set of MRP parameters either a production order has already been released with the forecasted and therefore incorrect order amount or the production order will be released with the realized and therefore correct order amount. It is assumed that customers do not change their orders after being stated.

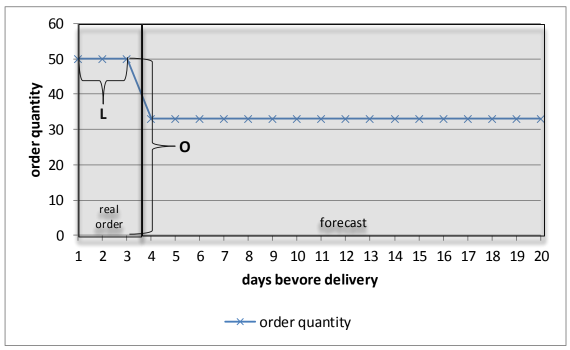


Figure 3: CRL order behavior

***FEV order behavior***

Figure 4 illustrates the information progress of the FEV order behavior. In this case the customer provides the forecast horizon (e.g. 20 days) in advance of the real customer order due date a planned order amount (e.g. 33 pcs.). This order amount stays constant until the forecast evaluation horizon is reached. Between the forecast evolution horizon (e.g. 8 days) and the frozen zone (e.g. 2 days) the customer changes the order amount periodically. Figure 4 illustrates a change frequency on a daily basis. Per change the forecast error $\varepsilon_p$ which is an identically independent truncated-normal-distributed random variable with an expected value $E[\varepsilon_p] = 0$ and variance $Var[\varepsilon_p] = (\delta \bar{d}_p)^2$ is added to the actual order amount. The parameter $\delta$ defines the variance of the forecast error and is independent of time period $t$ and item $p$. Within the frozen zone the customer order amount stays stable. Assuming that the error terms are independent of each other (this is the crucial assumption which is in the specific application slightly violated, see numerical study) leads to the following equation for the customer order of item $p$ and subperiod $\tau$ (day or due date).

$$O_{p,\tau,1,} = \bar{d}_p + \sum_{k=1}^{h-fz} \varepsilon_k \quad (9)$$

Here $\bar{d}_p$ is the constant demand forecast of item $p$ and due date $\tau$, $h$ is the forecast evolution horizon and $fz$ is the frozen zone.

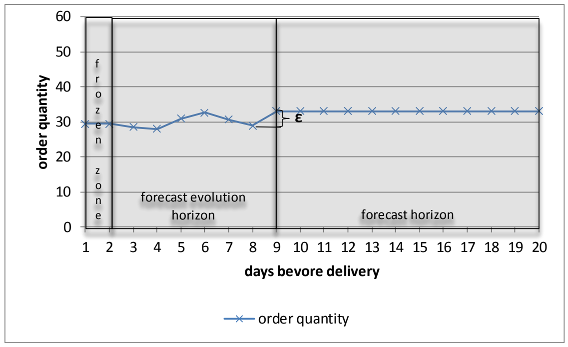


**Figure 4: FEV order behavior**

For the conducted simulation study we use a forecast evolution horizon $h$ of eight time periods, a frozen zone *fz* of two periods and a daily change frequency.

***Forecast quality measure β***

Due to the fact that the presented forecast error variables are completely different in both order behavior scenarios a normalized forecast quality measure $\beta$ is introduced to compare the performance of the FEV and the CRL scenarios within the MRP II approach. The development of the forecast quality measure is one of the major contributions of the paper. The standardized forecast quality measure per due date $\tau$ and sales product $p$ is defined as:

$$FQ_{p,\tau} = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(O_{p,\tau,1} - O_{p,\tau,i})^2}}{\bar{d}_p} \qquad \begin{array}{l} p = 1, \dots, P \\ \tau = 1, \dots, \Delta \end{array} \tag{10}$$

Here $\bar{d}_p$ is the constant demand forecast of item $p$ and due date $\tau$, $n$ is the sum of planned lead times over the low level codes, $O_{p,\tau,1}$ is the realized customer order at due date $\tau$ and $O_{p,\tau,i}$ is the planed order amount *i-1* periods before the required due date. Averaging the forecast quality values over all due dates $\tau$ (with limit $\Delta$, i.e. 365 days for one year) and items $p$ results in the overall forecast quality measure $\beta$.

$$\beta = \frac{\sum_{\tau=1}^{\Delta}\sum_{p=1}^{P} FQ_{p,\tau}}{\Delta * P} \tag{11}$$

$\beta$ describes the variance of MRP gross requirements compared to the realized demand occurrence (which is the final gross requirement) and is therefore a measure for the information dynamics and uncertainty the planning approach has to deal with. A $\beta$-value of zero means that the order amounts used for planning are exactly the same than the later realized customer orders (perfect forecast quality). A high $\beta$-value means a poor forecast quality.

Two additional measures are introduced to standardize and compare the two order behaviors. Firstly the average demand per day $\bar{d}$ is defined as

$$\bar{d} = E[O_{\tau,1}] = \frac{\sum_{\tau=1}^{\Delta}\sum_{p=1}^{P} O_{p,\tau,1}}{\Delta * P} \tag{12}$$

and secondly the variance of order demand per day

$$Var[O_{\tau,1}] = \frac{1}{\Delta-1}\sum_{\tau=1}^{\Delta}\left(\left(\sum_{p=1}^{P} O_{p,\tau,1}\right) - \bar{d}\right)^2. \tag{13}$$

In the numerical study we use tuples of similar forecast quality $\beta$, equal expected demand per day $E[O_{\tau,1}]$ and similar variance of the daily demand $Var[O_{\tau,1}]$ to compare the FEV and the CRL order behavior. To get appropriate levels of the latter explained tuples for the CRL order behavior the parameter α is varied and E[L] as well as $Var[O_{\tau,1}]$ have been identified in preliminary studies. For the FEV-scenario $\delta$ is varied and forecast evolution horizon $h$, change frequency and frozen zone $fz$ have been identified in a preliminary study.

## 4 NUMERICAL RESULTS

The cost objective in this study is the average overall costs per day separated into inventory, tardiness, internal capacity and external capacity costs. Customer orders that cannot be fulfilled at the end of the simulation time lead to extra costs in the form of penalties for their delay. The numerical study investigates the two different order behaviors FEV and CRL where the approximately optimal planned utilization factor $\eta_{opt}$ is found by enumeration (25 possible $\eta$-values between 0.55 and 1 are tested) for the respective forecast quality tuple ($\beta$, $E[O_{\tau,1}]$, $Var[O_{\tau,1}]$). A set of different forecast quality tuples ranging from high to medium forecast quality are studied. In the further course of the paper the expression optimal- overall costs / planned utilization factor / service level is a synonym for the best value found using the latter described enumeration. Additionally, the capacity demand $\rho$ (required capacity per year divided by available capacity per shift and year) is varied between low (Ø 2.2 shifts), medium (Ø 2.5 shifts) and high (Ø 2.8 shifts) situations. The processing times are adjusted to reach the different capacity demand levels whereby the customer demand quantities stay equal. For the medium term planning method MRP, planned lead times of 2 periods for all materials have been identified in a preliminary study, again applying enumeration schemes to find appropriate values, and are not changed within the simulation study. Since no setup times are modeled the lot sizing policy lot-for-lot is applied in MRP. No safety stocks have been used in this study. The ratio of the inventory cost rate $c^h$ to the tardiness cost rate $c^b$ is chosen to be 1:9 for the low level, 1:19 for the medium level and 1:99 for the high level. The ratio of the internal and external capacity costs is $c^i\ /c^e$ =1/2. For a scenario with low capacity costs the internal cost rate $c^i$ is 50 currency units per hour (CU/h) of the provided capacity and the external cost rate $c^e$ is 100 CU/h, for medium capacity costs $c^i$ is 100 CU/h and $c^e$ is 200 CU/h and for high capacity costs $c^i$ is 200 CU/h and $c^e$ is 400 CU/h. The inventory costs are equal for all scenarios and are determined to 1 CU for items 1x and 0.5 CU for materials 2x and 3x per day and unit. In the numerical studies, four whole years are simulated with the above described annual forecast / demand behavior, whereby the first year is the warm up time of the simulation model and therefore excluded from the analysis. Each parameter set is simulated with 10 replications.

***Influence of the Forecast quality measure β for the FEV and CRL order behavior***

Based on a full-factorial design of the above mentioned parameters, the best overall costs, the respective optimal planned utilization factor $\eta_{opt}$ and the respective service level are discussed for the FEV and CRL order behavior by comparing different levels of the forecast quality measure $\beta$. The range of $\beta$ is between 0.13 and 0.39. Table 1 shows the arithmetic mean of the optimal overall costs (over all parameter combinations) for the FEV order behavior in Table 1a and for the CRL order behavior quoted inTable 1b. The tables Table 1a and Table 1b each consists of three sub tables for the parameters $\rho$, $\{c^i, c^e\}$ and $c^b$.The bold row at the bottom of each sub table is the arithmetic mean of the respective $\beta$ value and the bold column on the right hand side of the sub table is the arithmetic mean of the respective parameter level. In the bottom right hand corner of the three sub tables the arithmetic mean of the overall costs of the whole CRL and FEV scenario is quoted. Table 2 and Table 3 use the same table structure but instead of overall costs, the optimal planned utilization factor $\eta_{opt}$ and the respective service level are presented with respect to the varying $\beta$ value and the three levels of the parameters capacity demand, capacity cost rate and tardiness cost rate.

Table 1: Optimal overall costs with respect to $\beta$ for the FEV and CRL order behavior.

a.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\rho$ | 2.2 | 11,790 | 11,838 | 11,921 | 11,997 | 12,096 | 12,182 | 12,278 | 12,399 | 12,487 | 12,617 | 12,713 | **12,211** |
| | 2.5 | 13,089 | 13,152 | 13,223 | 13,269 | 13,307 | 13,391 | 13,440 | 13,499 | 13,530 | 13,601 | 13,663 | **13,378** |
| | 2.8 | 13,688 | 13,709 | 13,753 | 13,758 | 13,843 | 13,904 | 14,090 | 14,246 | 14,460 | 14,663 | 14,909 | **14,093** |
| | Ø | **12,856** | **12,899** | **12,966** | **13,008** | **13,082** | **13,159** | **13,269** | **13,382** | **13,492** | **13,627** | **13,762** | **13,227** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\{c^i, c^e\}$ | low | 6,439 | 6,474 | 6,525 | 6,556 | 6,623 | 6,671 | 6,733 | 6,805 | 6,886 | 6,958 | 7,032 | **6,700** |
| | med | 11,287 | 11,326 | 11,377 | 11,399 | 11,475 | 11,547 | 11,678 | 11,750 | 11,868 | 11,976 | 12,121 | **11,619** |
| | high | 20,840 | 20,899 | 20,995 | 21,069 | 21,148 | 21,260 | 21,397 | 21,590 | 21,722 | 21,948 | 22,132 | **21,364** |
| | Ø | **12,856** | **12,899** | **12,966** | **13,008** | **13,082** | **13,159** | **13,269** | **13,382** | **13,492** | **13,627** | **13,762** | **13,227** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $c^b$ | low | 12,600 | 12,622 | 12,670 | 12,706 | 12,766 | 12,803 | 12,892 | 12,964 | 13,027 | 13,139 | 13,237 | **12,857** |
| | med | 12,781 | 12,824 | 12,892 | 12,935 | 13,003 | 13,082 | 13,185 | 13,265 | 13,352 | 13,475 | 13,598 | **13,127** |
| | high | 13,185 | 13,252 | 13,335 | 13,382 | 13,478 | 13,592 | 13,731 | 13,916 | 14,097 | 14,268 | 14,450 | **13,699** |
| | Ø | **12,856** | **12,899** | **12,966** | **13,008** | **13,082** | **13,159** | **13,269** | **13,382** | **13,492** | **13,627** | **13,762** | **13,227** |

b.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\rho$ | 2.2 | 11,282 | 11,440 | 11,823 | 12,242 | 12,683 | 13,091 | 13,437 | 13,911 | 14,187 | 14,395 | 15,143 | **13,058** |
| | 2.5 | 12,717 | 12,828 | 13,053 | 13,353 | 13,656 | 14,157 | 14,864 | 15,702 | 16,221 | 16,607 | 17,719 | **14,625** |
| | 2.8 | 13,426 | 13,457 | 13,542 | 14,271 | 15,305 | 16,370 | 17,304 | 18,495 | 19,079 | 19,407 | 20,925 | **16,507** |
| | Ø | **12,475** | **12,575** | **12,806** | **13,289** | **13,881** | **14,540** | **15,202** | **16,036** | **16,496** | **16,803** | **17,929** | **14,730** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\{c^i, c^e\}$ | low | 6,164 | 6,263 | 6,414 | 6,736 | 7,074 | 7,435 | 7,782 | 8,193 | 8,454 | 8,546 | 9,271 | **7,485** |
| | med | 10,921 | 11,015 | 11,239 | 11,695 | 12,219 | 12,842 | 13,431 | 14,231 | 14,632 | 14,899 | 16,015 | **13,013** |
| | high | 20,341 | 20,446 | 20,765 | 21,434 | 22,350 | 23,342 | 24,392 | 25,684 | 26,401 | 26,964 | 28,501 | **23,693** |
| | Ø | **12,475** | **12,575** | **12,806** | **13,289** | **13,881** | **14,540** | **15,202** | **16,036** | **16,496** | **16,803** | **17,929** | **14,730** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $c^b$ | low | 12,232 | 12,329 | 12,496 | 12,843 | 13,291 | 13,791 | 14,325 | 15,000 | 15,259 | 15,624 | 16,268 | **13,951** |
| | med | 12,400 | 12,490 | 12,693 | 13,132 | 13,683 | 14,280 | 14,914 | 15,686 | 16,104 | 16,495 | 17,486 | **14,488** |
| | high | 12,793 | 12,905 | 13,229 | 13,891 | 14,671 | 15,548 | 16,366 | 17,422 | 18,123 | 18,291 | 20,034 | **15,752** |
| | Ø | **12,475** | **12,575** | **12,806** | **13,289** | **13,881** | **14,540** | **15,202** | **16,036** | **16,496** | **16,803** | **17,929** | **14,730** |

The study shows that the overall costs illustrated in Table 1 have a positive correlation with the forecast quality measure $\beta$. There is also a positive correlation between the overall costs and the demand $\rho$, the capacity cost rates $\{c^i, c^e\}$ and the tardiness cost rate $c^b$.

The average of overall costs of the FEV order behavior (Table 1a) is 13,227 CU and the overall costs of the CRL order behavior is 11.4% higher which leads to overall cost of 14,730 (Table 1b). The study shows that for the same level of the forecast quality measure $\beta$ the hierarchical production planning approach MRP II performs for the FEV order behavior better than for the CRL order behavior. It can therefore be stated that the MRP II structure handles small, continuous changes in the FEV-scenario far better than a unique, short term change in order amount.

A cost reduction potential of 6.6% comparing the overall costs of $\beta$=0.13 and $\beta$=0.39 for the FEV-scenario is identified in contrast to the CRL order behavior where the cost reduction potential is 43.7%. One finding from comparing the FEV and CRL order behavior for different levels of information dynamics and uncertainty is that the MRP II structure handles small, continuous changes of order amounts in the FEV-scenario far better than the unique, short term changes in the CRL behavior.

Table 2: Optimal planned utilization factor $\eta_{opt}$ with respect to $\beta$ for the FEV and CRL order behavior.

a.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\rho$ | 2.2 | 0.90 | 0.89 | 0.88 | 0.88 | 0.87 | 0.86 | 0.86 | 0.85 | 0.85 | 0.83 | 0.82 | **0.86** |
| | 2.5 | 0.89 | 0.88 | 0.88 | 0.87 | 0.87 | 0.86 | 0.86 | 0.84 | 0.84 | 0.84 | 0.83 | **0.86** |
| | 2.8 | 0.90 | 0.90 | 0.90 | 0.90 | 0.89 | 0.89 | 0.89 | 0.88 | 0.88 | 0.87 | 0.86 | **0.89** |
| | Ø | **0.90** | **0.89** | **0.88** | **0.88** | **0.88** | **0.87** | **0.87** | **0.86** | **0.85** | **0.85** | **0.84** | **0.87** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\{c^i, c^e\}$ | low | 0.90 | 0.89 | 0.88 | 0.88 | 0.87 | 0.86 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | **0.86** |
| | med | 0.89 | 0.89 | 0.88 | 0.88 | 0.88 | 0.87 | 0.86 | 0.86 | 0.86 | 0.84 | 0.84 | **0.87** |
| | high | 0.90 | 0.90 | 0.89 | 0.89 | 0.89 | 0.88 | 0.88 | 0.87 | 0.87 | 0.87 | 0.86 | **0.88** |
| | Ø | **0.90** | **0.89** | **0.88** | **0.88** | **0.88** | **0.87** | **0.87** | **0.86** | **0.85** | **0.85** | **0.84** | **0.87** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $c^b$ | low | 0.92 | 0.91 | 0.91 | 0.91 | 0.90 | 0.90 | 0.90 | 0.89 | 0.89 | 0.88 | 0.88 | **0.90** |
| | med | 0.90 | 0.90 | 0.89 | 0.89 | 0.89 | 0.89 | 0.88 | 0.87 | 0.86 | 0.85 | 0.85 | **0.88** |
| | high | 0.87 | 0.86 | 0.85 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81 | 0.80 | 0.79 | **0.83** |
| | Ø | **0.90** | **0.89** | **0.88** | **0.88** | **0.88** | **0.87** | **0.87** | **0.86** | **0.85** | **0.85** | **0.84** | **0.87** |

b.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\rho$ | 2.2 | 0.93 | 0.92 | 0.89 | 0.85 | 0.82 | 0.78 | 0.76 | 0.73 | 0.71 | 0.70 | 0.68 | **0.80** |
| | 2.5 | 0.93 | 0.92 | 0.88 | 0.86 | 0.83 | 0.81 | 0.78 | 0.74 | 0.72 | 0.71 | 0.68 | **0.81** |
| | 2.8 | 0.95 | 0.94 | 0.93 | 0.89 | 0.85 | 0.81 | 0.78 | 0.72 | 0.70 | 0.69 | 0.63 | **0.81** |
| | Ø | **0.93** | **0.93** | **0.90** | **0.87** | **0.83** | **0.80** | **0.77** | **0.73** | **0.71** | **0.70** | **0.66** | **0.80** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $\{c^i, c^e\}$ | low | 0.94 | 0.92 | 0.89 | 0.85 | 0.81 | 0.78 | 0.74 | 0.70 | 0.68 | 0.66 | 0.61 | **0.78** |
| | med | 0.93 | 0.92 | 0.90 | 0.86 | 0.83 | 0.80 | 0.77 | 0.73 | 0.71 | 0.69 | 0.66 | **0.80** |
| | high | 0.93 | 0.93 | 0.91 | 0.88 | 0.86 | 0.83 | 0.80 | 0.76 | 0.75 | 0.75 | 0.71 | **0.83** |
| | Ø | **0.93** | **0.93** | **0.90** | **0.87** | **0.83** | **0.80** | **0.77** | **0.73** | **0.71** | **0.70** | **0.66** | **0.80** |
| | | $\beta$ | | | | | | | | | | | |
| | | 0.13 | 0.16 | 0.18 | 0.21 | 0.24 | 0.27 | 0.29 | 0.32 | 0.35 | 0.37 | 0.39 | Ø |
| $c^b$ | low | 0.96 | 0.95 | 0.93 | 0.90 | 0.87 | 0.84 | 0.82 | 0.78 | 0.77 | 0.76 | 0.74 | **0.85** |
| | med | 0.94 | 0.93 | 0.92 | 0.87 | 0.85 | 0.81 | 0.78 | 0.75 | 0.73 | 0.71 | 0.68 | **0.81** |
| | high | 0.91 | 0.90 | 0.86 | 0.82 | 0.79 | 0.75 | 0.72 | 0.66 | 0.64 | 0.63 | 0.57 | **0.75** |
| | Ø | **0.93** | **0.93** | **0.90** | **0.87** | **0.83** | **0.80** | **0.77** | **0.73** | **0.71** | **0.70** | **0.66** | **0.80** |

Table 2 shows that the optimal planned utilization factor $\eta_{opt}$ has a negative correlation with respect to $\beta$. This leads to the finding that higher forecast quality variance has to be compensated by additional excess capacity which has to be considered as soon as in the aggregate planning phase.

The results illustrate that the capacity demand $\rho$ has no systematic influence on $\eta_{opt}$. There is a positive correlation of the internal planned utilization factor and the increasing capacity cost rates $\{c^i, c^e\}$

for high $\beta$ values. This finding supports previous literature stating that the more expensive capacity is, the higher the production system utilization should be (see e.g. Jodlbauer and Altendorfer 2010). Based on this finding, an intuitive result is that a higher tardiness cost rate $c^b$ leads to lower optimal internal production system utilization $\eta_{opt}$.

For the FEV order behavior, the average planned utilization factor is 87% and 80% for the CRL order behavior. This finding is in line with the lower overall costs for the FEV-system being able to work with higher utilization. Latter is accompanied by the finding that an absolute difference in optimal production system utilization of 6%/27% is found between $\beta$=0.13 and $\beta$=0.39 of the FEV/CRL order behavior respectively.

Table 3: Optimal service level with respect to $\beta$ for the FEV and CRL order behavior.

a.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $\rho$ | *2.2* | 0.91 | 0.91 | 0.92 | 0.92 | 0.92 | 0.91 | 0.91 | 0.91 | 0.91 | 0.92 | 0.92 | **0.92** |
| | *2.5* | 0.92 | 0.92 | 0.92 | 0.91 | 0.92 | 0.91 | 0.93 | 0.94 | 0.94 | 0.93 | 0.94 | **0.93** |
| | *2.8* | 0.99 | 0.99 | 0.99 | 0.99 | 0.98 | 0.97 | 0.95 | 0.94 | 0.92 | 0.92 | 0.90 | **0.96** |
| | **Ø** | **0.94** | **0.94** | **0.94** | **0.94** | **0.94** | **0.93** | **0.93** | **0.93** | **0.92** | **0.92** | **0.92** | **0.93** |

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $\{c^i,c^e\}$ | *low* | 0.96 | 0.96 | 0.96 | 0.95 | 0.96 | 0.95 | 0.95 | 0.95 | 0.95 | 0.95 | 0.95 | **0.95** |
| | *med* | 0.94 | 0.94 | 0.95 | 0.94 | 0.95 | 0.93 | 0.93 | 0.93 | 0.92 | 0.93 | 0.93 | **0.94** |
| | *high* | 0.92 | 0.92 | 0.92 | 0.92 | 0.91 | 0.91 | 0.91 | 0.91 | 0.90 | 0.89 | 0.89 | **0.91** |
| | **Ø** | **0.94** | **0.94** | **0.94** | **0.94** | **0.94** | **0.93** | **0.93** | **0.93** | **0.92** | **0.92** | **0.92** | **0.93** |

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $c^b$ | *low* | 0.90 | 0.90 | 0.90 | 0.90 | 0.89 | 0.89 | 0.88 | 0.88 | 0.87 | 0.87 | 0.87 | **0.89** |
| | *med* | 0.94 | 0.93 | 0.94 | 0.93 | 0.93 | 0.92 | 0.93 | 0.93 | 0.92 | 0.93 | 0.92 | **0.93** |
| | *high* | 0.98 | 0.99 | 0.99 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.98 | 0.97 | 0.97 | **0.98** |
| | Ø | **0.94** | **0.94** | **0.94** | **0.94** | **0.94** | **0.93** | **0.93** | **0.93** | **0.92** | **0.92** | **0.92** | **0.93** |

b.

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $\rho$ | *2.2* | 0.94 | 0.93 | 0.94 | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 | 0.93 | 0.92 | 0.91 | **0.93** |
| | *2.5* | 0.92 | 0.92 | 0.93 | 0.94 | 0.94 | 0.93 | 0.92 | 0.90 | 0.90 | 0.88 | 0.87 | **0.91** |
| | *2.8* | 0.98 | 0.98 | 0.98 | 0.93 | 0.90 | 0.89 | 0.89 | 0.91 | 0.89 | 0.89 | 0.91 | **0.92** |
| | **Ø** | **0.94** | **0.94** | **0.95** | **0.94** | **0.92** | **0.92** | **0.91** | **0.91** | **0.91** | **0.90** | **0.89** | **0.92** |

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $\{c^i,c^e\}$ | *low* | 0.97 | 0.96 | 0.97 | 0.96 | 0.95 | 0.95 | 0.94 | 0.95 | 0.94 | 0.94 | 0.94 | **0.95** |
| | *med* | 0.94 | 0.94 | 0.95 | 0.94 | 0.94 | 0.92 | 0.92 | 0.91 | 0.92 | 0.91 | 0.90 | **0.93** |
| | *high* | 0.92 | 0.92 | 0.93 | 0.91 | 0.88 | 0.88 | 0.87 | 0.88 | 0.87 | 0.84 | 0.84 | **0.89** |
| | **Ø** | **0.94** | **0.94** | **0.95** | **0.94** | **0.92** | **0.92** | **0.91** | **0.91** | **0.91** | **0.90** | **0.89** | **0.92** |

| | | $\beta$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *0.13* | *0.16* | *0.18* | *0.21* | *0.24* | *0.27* | *0.29* | *0.32* | *0.35* | *0.37* | *0.39* | **Ø** |
| $c^b$ | *low* | 0.90 | 0.89 | 0.92 | 0.89 | 0.88 | 0.86 | 0.85 | 0.86 | 0.85 | 0.82 | 0.82 | **0.87** |
| | *med* | 0.95 | 0.95 | 0.94 | 0.93 | 0.92 | 0.92 | 0.91 | 0.90 | 0.90 | 0.90 | 0.89 | **0.92** |
| | *high* | 0.99 | 0.98 | 0.99 | 0.98 | 0.97 | 0.97 | 0.97 | 0.98 | 0.97 | 0.97 | 0.97 | **0.98** |
| | Ø | **0.94** | **0.94** | **0.95** | **0.94** | **0.92** | **0.92** | **0.91** | **0.91** | **0.91** | **0.90** | **0.89** | **0.92** |

For the FEV and CRL order behavior illustrated in Table 3a and b, we conjecture, that the optimal service level is non-increasing with increasing $\beta$ value. From a customer's point of view this leads to the finding that worse forecasts with more variance provided to the supplier imply an increasing risk of observing a lower service level performance from this supplier. Furthermore, the study confirms the intuitive results that the optimal service level decreases with a higher weighting of capacity cost rates $\{c^i, c^e\}$ and increases with a higher weighting of tardiness cost rate $c^b$.

## 5 CONCLUSION

In this paper the effect of two different order behaviors within a hierarchical production planning system (MRP II) is investigated. The simulation study conducted shows that excess capacity is needed to mitigate the effect of assuming a deterministic setting in the APP optimization problem but facing stochastic shop floor behavior. It is shown that the excess capacity needed increases with respect to decreasing forecast quality. This excess capacity has already to be included in the APP and an approach with a planned utilization factor defining the internal capacity is therefore presented in this paper. The overall costs are found to significantly increase with decreasing forecast quality (consistent over all parameter settings). The contribution of this study lies in, the modeling of the FEV and CRL order behavior, the development of a normalized forecast quality measure and finally the investigation on how the MRP II structure mitigates different information dynamics and uncertainties comparing the two order behaviors. We find that for lower forecast quality, the CRL order behavior leads to significantly higher costs than the FEV order behavior. The study shows that even in this rather robust MRP II system a high cost reduction potential is linked to information dynamics reduction. Further research could extend the current study by investigating different demand patterns and production structures. Additionally the influence of the CRL and FEV parameter on forecast quality could be analyzed in a more detailed way.

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