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SIMULATING THE IMPACT OF FORECAST RELATED OVERBOOKING AND UNDERBOOKING BEHAVIOR ON MRP PLANNING AND A REORDER POINT SYSTEM

Wolfgang Seiringer
Klaus Altendorfer

Department for Production and
Operation Management
University of Applied Sciences Upper Austria
Wehrgrabengasse 1-3
A-4400 Steyr, AUSTRIA

Thomas Felberbauer

Department of Media and
Digital Technologies
University of Applied Sciences St. Pölten
Campus-Platz 1
A-3100 St. Pölten, AUSTRIA

ABSTRACT

Production Planning and its parameterization is critical to fulfil customer demands and to successfully react on changes in high volatile markets. Therefore, demand updates should be considered to improve production planning. In this paper the performance of two production planning methods MRP (Material Requirements Planning) and RPS (Reorder Point System) are compared in a multi-item single stage system where customer orders are updated in a rolling horizon manner. Applying a simulation study, we investigate the performance of MRP and RPS for biased and unbiased forecast information and discuss the difference in the optimal planning parameters. The study shows that for a production system with underbooking and low demand uncertainty, RPS method is superior, in all other scenarios MRP outperforms RPS. For overbooking scenarios, the results show MRP leads to overall cost improvements ranging from 8 to 30 %.

1 INTRODUCTION

From a production planning and scheduling perspective, the worldwide crises since 2020 showed the necessity for manufacturers from different fields to be resilient against heavily fluctuating demands. As a result, some companies were confronted with customers supplying demand forecasts which lead to an overestimation or underestimation of the realized demand. In the context of demand forecasting this can be related to overbooking or underbooking behavior. Especially when customers change their demand for a respective due date, the production planning task becomes complicated. In this article, the focus is on overbooking and underbooking behavior of customers, this means the long-term forecast is lower or higher compared to the actual customer demand, see also Zeiml et al. (2019). Forecasting can be split up in systematic behavior and unsystematic disturbances, whereby underbooking and overbooking are part of systematic forecast behaviors (Heath and Jackson 1994). Independent of a forecast behavior, changing customer demand forecasts introduce uncertainty into the underlying production system. Two widely applied methods to plan the production are Material Requirements Planning (MRP) and Reorder Point Systems (RPS), compare to Hopp and Spearman (2011) and Silver et al. (1998). Both approaches follow simple rules and are applicable independent of the underlying production system. For MRP, based on the gross requirements of future periods, the steps: netting, lot-sizing, time phasing, and bill of material (BOM) explosion are applied, see Hopp and Spearman (2011). For RPS, a new production order is issued whenever the inventory position falls below the reorder point, see Hopp and Spearman (2011). This short explanation already shows one main difference between MRP and RPS, i.e., MRP uses demand forecast data (included in the gross requirements of end items) for planning and RPS not. For MRP, the three parameters safety stock, lot policy, and planned lead time must be set and for the reorder point system lot size and reorder

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point is necessary to configure the method. Different studies from literature show that including accurate customer demand information into the production planning leads to a cost reduction; see Wijngaard (2004), Benjaafar et al. (2011), and Altendorfer and Minner (2014) studying different RPS systems extended by advance demand information and Enns (2001) as well as Altendorfer (2019) studying MRP. This means that MRP has a superior performance in comparison to standard RPS (without advance demand information) if forecast demand information is perfect. However, when uncertain forecasts occur, the performance of MRP decreases; see Enns (2002) and Altendorfer et al. (2016) for MRP effects as well as Altendorfer and Felberbauer (2023) for detailed forecast error analysis. If demand forecasts are updated regularly including unsystematic error and a systematic bias occurs, i.e., overbooking or underbooking, the performance of MRP suffers significantly as the performance gain by applying future demand information diminishes. Therefore, this article compares the performance of MRP and standard RPS (without advance demand information) under forecast related demand uncertainty by means of simulation. The overall costs applied for performance measurement consist of inventory and backorder costs. For the simulation study, a simple multi-item single-stage production systems is used. In this paper we investigate if an increasing forecast bias hinders the performance of the MRP algorithm. As higher unsystematic forecast errors negatively influence both, RPS and MRP, we conjecture that overall costs increase with increasing uncertainty for both methods. In detail, the following research questions are addressed:

RQ1: *What is the difference in performance of MRP compared to RPS if uncertain forecasts occur with regular updates that are unbiased?*
RQ2: *What is the influence of overbooking and underbooking on the performance of MRP and RPS if uncertain forecasts with regular updates occur?*
RQ3: *What are optimal planning parameters for MRP compared to RPS for the above-mentioned scenarios? Are there significant differences in the respective planning parameters?*

To make a fair comparison, the planning parameters for MRP and RPS are optimized in a large numerical simulation study using a full factorial enumeration of feasible planning parameters identified in preliminary studies. RQ1 and RQ2 contribute to better understand how demand uncertainty influences the performance of well-established production planning and control systems. RQ3 provides managerial insights in how to set optimal parameters for different forecast behaviors.

2 RELATED LITERATURE

Different inventory policies with continuous or periodic review are covered in various articles (Axsäter 2007, Silver et al. 1998, Tempelmeier 2011). There are several papers where the assumption of stable uncorrelated demand is relaxed. Iyer and Schrage (1992) discuss a stochastic inventory model where time varying parameters depending on past empirical data. Janssen et al. (1998) and Janssen et al. (1999) critically discuss the effect of demand distribution assumptions on the realized service level within an (R, s, Q) inventory model and identify that distribution misspecification can have significant effects. Bertsimas and Thiele (2006) apply mixed-integer-linear programming (MILP) to optimize inventory model parameters based on empirical data, which leads to a distribution free solution reducing the assumptions needed in stochastic models. The literature stream focusing on "advance demand information" show that including accurate demand information improves performance (Altendorfer and Minner 2014; Benjaafar et al. 2011; Wijngaard 2004). Computing the ideal reorder point for reordering purchase items or reproducing self-produced items has already been investigated since several decades. It is still one of the most important planning decisions for the operation of a production system. This type of planning concept to avoid a stock out situation is related to so called reorder point systems also as known as (s,Q) system and is consumption driven (Silver et al. 1998). This means the reorder point is driven by customer consumption of sales items and sales items consuming components. Stock out situations are tried to avoid, due to decreasing service level and can lead to lost sales costs. Another well-known production scheduling approach is MRP with the main difference, that a planning horizon is used (Hopp and Spearman 2011). Literature on MRP shows that with accurate demand information, MRP performs well (Altendorfer 2019). However, demand updates simultaneously leads to uncertainty that dampens the performance of the production system (Ho and Ireland 1998; Li and Disney 2017). Several studies show that the forecast uncertainty in the supply chain leads to a significant performance loss of the MRP system (Altendorfer et al. 2016; Enns 2001, 2002). To model the setting with rolling forecast updates, forecast evolution models are an appropriate method to mimic such a common system (Heath and Jackson 1994; Norouzi and Uzsoy 2014). Altendorfer and Felberbauer (2023) study the influence of forecast error and forecast bias on forecast and production order accuracy assuming a streamlined MRP-System with one production planning level. They evaluate the performance of a correction model for real data and within a broad simulation study. Discrete Event Simulation is a well-established method to model the production system and discuss or optimize its performance for different system settings (Altendorfer et al. 2016; Altendorfer and Felberbauer 2023; Enns 2001; Juan et al. 2015). In this study we contribute to available literature as specifically the influence of regularly updated biased forecasts in a rolling horizon MRP planning environment is addressed and compared to RPS.

3 SIMULATION STUDY SETUP

To answer the research questions a simulation study is conducted. For meaningful performance evaluation, the simulation runtime per replication was set to 800 periods (days), including 160 periods for warm-up. After the 160 days all the statistics are reset, as steady state of the simulation systems is assumed. This simulation runtime allows to investigate the evaluated production planning approach for two years with a daily planning frequency. Uncertainty is firstly included into the forecasting process of customer demand, and secondly, a stochastic setup time is applied. Processing time of items is considered to be deterministic assuming a stable production process. To account for stochastic effects, 10 replications were used for each iteration. The core components of the discrete-event simulation model are the (1) *demand generation* component, (2) *production scheduling* component, (3) *stock booking* component, (3) *job shop processing* component and (4) the *database* component. At first the production system is loaded once per simulation run using the database component. The database component stores the master data: Bill of Material (BOM), routing data, demand parameters, and basic setting for the simulation experiment. The production scheduling component knows from the master data, which production planning and scheduling method should be applied for the current simulation run and the demand scenario (forecasting) parameters. For this simulation study, standard MRP or standard RPS can be selected for the items of the BOM. After getting the simulation experiment settings from the database component, the next step in the simulation model is to start periodic demand generation using the described forecasting approach. The selected planning type is conducted periodically, demand and production planning methods are calculated every period (day). The production scheduling component takes the demand and generates a production schedule, which provides the release dates and quantities for the subsequent job shop processing. When a production order reaches its start date, the material release method is called and checks if enough quantity for the item of the production order is on stock. If enough inventory is on stock, the production order is passed to the machine queue, where job shop processing is done. For the current simulation study, the production orders are processed according to the planned start date. This means independent of the production lot size, the next order is selected from the queue and passed to the machine delay block for processing the item. Finally, the produced quantity is put on stock. In the moment of stock booking, the customer orders are queried to fulfill customer demand and material release is checked to release the next production order. This demand generation, production scheduling, and job shop processing cycle is done until the simulation time ends.

3.1 Production System

For the simulation study, Figure 1 shows the simple multi-item and single-stage production systems which is evaluated using the developed discrete event simulation framework. On the top level of the BOM (Bill of Material) with LLC=0 the sales items 10 and 20 are located. Both sales items are produced on resource (machine) M1. Item 10 and item 20 both require raw material 100 from LLC = 1. To produce one unit of item 10, one unit of item 100 is required, the same relation holds for item 20 and 100. The raw material 100 is regarded as always available. This means between LLC 0 and LLC 1, a delay due to unavailable raw material is not possible. This simple production system allows to meaningfully investigate the planning behavior of MRP and RPS, with the focus on forecast introduced demand uncertainty. Note that a multi-stage production system might lead to additional insights, however, it would require identifying and setting up planning methods MRP or RPS for the underlying components with suitable planning parameters. This task is out of scope for this article as the single-stage production system perfectly reflects the core research target of a fair MRP to RPS performance comparison with focus on forecast related demand uncertainty. However, more complex production system structures with more items and multiple production stages will be investigated in future research.

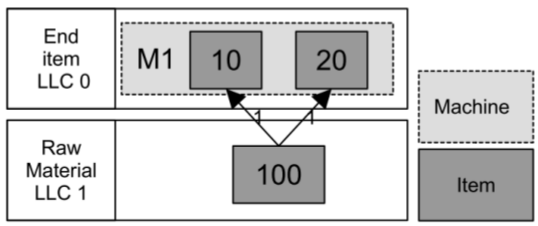

Figure 1: Bill of materials and production system.

The average demand processed by the system simulation model is set to 800 pieces per period and per item, the associated processing time per item for the investigated utilization levels {90 %, 95 %, 98 %} is set deterministic with {0.675, 0.72, 0.747} minutes. The setup time of each production order is stochastic with an expected value of 108 minutes. For setup time, the coefficient of variation is set to 0.5. This deterministic processing and stochastic setup time is a practically interesting case, as it is more likely to have uncertain setup times but processing itself is often deterministic; especially when the same items are produced for longer time on a machine. For a daily capacity of 1440 minutes per machine and a production lot size of 800 pieces for each item, i.e., one production order per item each day, this leads to an average utilization of {90 %, 95 %, 98 %} whereby {75 %, 80 %, 83 %} are processing and 15 % are setup. These scenarios include different levels of unused capacity which enables additional orders to compensate forecast updates in MRP, however, the shop load is still high enough to create significant production lead times influencing the reorder point in RPS and the planned lead time as well as the safety stock in MRP. Note that different lot sizes and additional orders based in forecast updates lead to utilization values different from the 90 %, 95 % and 98 %, therefore, we refer to these three scenarios as low, medium, and high shop load.

3.2 Reorder Point System (RPS) Integration

When applying the standard RPS (as we do in this paper), always the current period t is relevant, and no demand forecast is applied for issuing the production orders. This means the inventory position $IP_{t,g}$ for period t and item g is computed using equation (1).

$$IP_{t,g} = S_{t,g} + O_{t,g} - B_{t,g} \tag{1}$$

In the context of a production system simulation, this means at time period t of the simulation run, the values for on stock inventory $S_{t,g}$, open deliveries $O_{t,g}$, and backorders $B_{t,g}$ for item g are computed. Looking on the production system structure represented by the BOM, compare to Figure 1, they must be mapped to the correct entities in the simulation model. Even though, the current study does not include components to be planned, they are included in the following description, as our simulation model is also capably of simulating complex multi-stage production systems. In our production system context, end items and components are produced on machines and raw materials must be purchased. The variable $S_{t,g}$ represents number of units physically on stock at period t, independent if the item is a sales item, a component, or a raw material. The $O_{t,g}$ quantity represents all open production orders at period t for item g, i.e., including sales items and components, which are not finished. For the backorders $B_{t,g}$, a difference between sales items and components must be made. For sales items, all customer orders with a due date $<t$, that are not yet fulfilled, are summed up for $B_{t,g}$. For components, all production orders for sales items that have not yet received the respective raw materials are summed up for $B_{t,g}$. A new production order with start date t and planned end date $t + PLT_g$ (planned lead time for item g) is created and passed to the material release component, when $IP_{t,g} < RP_g$; whereby RP_g is the reorder point for item g. For the RPS, the planned end date does not affect the planning result, but it is necessary for the subsequent KPI computation within the generic simulation framework.

3.3 Material Requirements Planning (MRP) Integration

Standard MRP is the second production planning approach, which is implemented in the production scheduling component. A major difference between RPS and MRP is the application of a planning horizon for MRP, within which the demand forecasts are used as input for creating production orders. All demand forecasts (gross requirements) which are within this pre-defined planning horizon, are part of the standard MRP steps. These steps are firstly, to apply the gross requirements for performing the netting, secondly apply the pre-set lot sizing policy, thirdly to do time phasing (i.e., backward scheduling in our model), and fourthly to calculate gross requirements for needed components and raw materials within the BOM explosion step. These steps are applied for the given items within the BOM beginning with the end items with low level code (LLC) of 0 until the last LLC with MRP planned components is reached, see also (Hopp and Spearman 2011) for details.

MRP is called at period t during the simulation runtime, all MRP planning steps are applied until $t+M$, with M being the planning horizon. The minimum length of the MRP planning horizon M is related to the sum of all planned lead times PLT_g for end items and the respective components as well as the applied lot sizing policy. We set M=20 which is sufficiently high to support the evaluated rolling horizon planning effects. An explanatory example of MRP planning starting at t=11 for item 10 and covering M=10 planning periods is shown in Table 1. At t=11, MRP planning is called in the simulation model performing the steps netting, lot sizing, time phasing, and BOM explosion. Computed gross requirements of end items are equal to demand forecasts at time t. *Projected On Hand* is the difference between the *Gross Requirements*, *Scheduled Receipts*, and *On Stock*. When *Projected On Hand* falls below the safety stock (which is zero in this example), a *Net Requirement* is observed, which must be covered by *Planned Order Receipts*. These *Planned Order Receipts* are computed based on the lot sizing policy. In the example, the lot sizing policy fixed order quantity (FOQ) with 800 units is used. After the *Planned Order Receipts* are computed, the associated *Planned Order Releases* are set based on the planned lead time for item 10 (PLT_{11}). In this case the PLT_{11}=1, this means the computed *Planned Order Release* quantity is released to the production one period before the respective due date. At first glance, the standard MRP logic seems to be very simple. It gets difficult when the interaction of the three planning parameters safety stock, lot sizing policy and planned lead time are investigated in the context of a production system. The conducted simulation experiment was run parallel as distributed experiments on 20 multi-core desktop computers with 16 GByte RAM. Using only one of these computers the runtime is approximately 30 days. To investigate a more complex production system in a reasonable timeframe, e.g. 7 to 14 days, in Seiringer et al. (2022a) a Simulation Budget Management (SBM) approach for full factorial design is applied. This approach is skipping the remaining replications of an iteration if the average costs of the current iteration are higher compared to already finished iterations. To avoid a full factorial design, in Seiringer et al. (2022b) a simulation heuristic applying simulation annealing (SA) is evaluated. Here the best solution (minimum costs) is searched by adaptively changing the MRP parameter space during simulation. Both methods can help to reduce simulation runtime and to identify minimum overall costs. Selecting appropriate MRP parameter ranges still depends on the parameter space and production system complexity. Both must be fit to the target of the simulation experiment. Therefore, the ranges of the tested MRP planning parameters were selected to get a simulation study covering a broad parameter range, but remain solvable in reasonable time.

Table 1: Example MRP planning at simulation runtime t=11.

MRP Period for Item = 10	*11.0-11.99*	*12.0-12.99*	*13.0-13.99*	*14.0-14.99*	*15.0-15.99*	*16.0-16.99*	*17.0-17.99*	*18.0-18.99*	*19.0-19.99*	*20.0-20.99*	*21.0-21.99*
Gross Requirements	942	744	748	745	928	773	783	975	814	807	800
Scheduled Receipts	800	0	0	0	0	0	0	0	0	0	0
Project On Hand	702	-42	-748	-745	-928	-773	-783	-975	-814	-807	-800
Net Requirements	0	42	748	745	928	773	783	975	814	807	800
Planned Order Receipts	0	800	0	800	1600	800	800	800	800	800	800
Planned Order Releases	800	0	800	1600	800	800	800	800	800	800	0
On Stock	844	0	0	0	0	0	0	0	0	0	0

3.4 Forecast Evolution Integration

To enable the evaluation of different forecast uncertainties and biased forecasts, i.e., overbooking and underbooking, the customer demands are generated based on the idea of the additive MMFE (martingale model of forecast evolution) model; compare to Heath and Jackson (1994) and Norouzi and Uzsoy (2014) for MMFE details. Equation (2) shows the demand forecast applied, whereby $D_{g,i,j}$ is the demand forecast of item g for due date i which is provided j periods before delivery. $\varepsilon_{g,i,j}$ is the random update term applied, and H is the forecast horizon. For periods above the forecast horizon, the customers provide a constant forecast and within H, each period one forecast update is performed. In the current simulation model, H=10 is applied, i.e., customers start to update their forecasts 10 periods before delivery and consequently 10 updates are performed. The random update term is defined in equation (3).

$$D_{g,i,j} = \begin{cases} x_g & \text{for } j > H \\ x_g + \varepsilon_{g,i,j} & \text{for } j = H \\ D_{g,i,j+1} + \varepsilon_{g,i,j} & \text{for } j < H \end{cases} \tag{2}$$

$$\varepsilon_{g,i,j} \sim N(\mu_\varepsilon, \sigma_\varepsilon);\ \mu_\varepsilon = \beta x_g;\ \sigma_\varepsilon = \alpha x_g \tag{3}$$

This modelling of $\varepsilon_{g,i,j}$ in Equation (3) implies that α specifies the level of unsystematic forecast uncertainty and β specifies the forecast bias. Note that for the forecast updates $\varepsilon_{g,i,j}$, a truncated normal distribution is applied to avoid negative demand forecast values, i.e., $\varepsilon_{g,i,j} > (-D_{g,i,j})$ and $\varepsilon_{g,i,j} < D_{g,i,j} + 2\mu_\varepsilon$. In the numerical study, several α and β values are tested to evaluate their influence. The expected order amount E[$D_{g,i,0}$] is set to 800 pcs/period for both items in this study. For biased forecasts, this implies that the long-term forecast x_g is lower than 800 pcs for underbooking and higher than 800 pcs for overbooking. Note that the truncation of $\varepsilon_{g,i,j}$ leads for biased settings to slight deviations in the expected order amount, which can be neglected regarding the focus of this study. For further details on the respective biased MMFE modeling please refer to Altendorfer and Felberbauer (2023).

3.5 Experiment Plan

The production system introduced in Figure 1 is simulated at low, medium, and high shop loads (see Section 3.1 for details) to identify the effect of shop congestion on the optimal planning methods and the respective parameters. The demand for the simulated production system is generated based on the forecasting behavior introduced in equations (2) and (3). For the demand information horizon of H=10 with long term forecast x_g=800, nine unbiased forecast uncertainty scenarios with α = {0, 0.025, 0.05, …, 0.2} and β = 0 are tested to evaluate the respective influence. To test overbooking, β = {-0.01, -0.02, …, -0.05} for α = {0.05, 0.1}, and to test underbooking, β = {0.01, 0.02, …, 0.05} for α = {0.05, 0.1}, are simulated in the numerical study. For the evaluated planning systems, their planning parameters are varied to perform a fair performance comparison. The respective parameter ranges have been identified in preliminary simulation runs. For RPS, the planning parameters varied are lot size *LS* and reorder point *RP*. For MRP, these are safety stock *SS*, lot sizing policy (with the respective parameter) and planned lead time *PLT*. For MRP the lot size policies of fixed order quantity (FOQ) with *LS* (lot size) as parameter and fixed order Period (FOP) with *NP* (number of periods) as parameter are evaluated. For both, MRP and RPS, the same planning parameters are applied for item 10 and 20. In detail, the MRP parameters have the following ranges: *SS*={0, 200, 400, 600, 800, 1200, 1600}, for FOQ *LS*={200, 400, 600, 800, 1200, 1600, 2400, 3200}, for FOP *NP*={1, 2, 3, 4, 5}, and *LT*={2, 4, 6, 8}. For RPS, the same lot sizes LS as for FOQ in MRP are used and *RP*={2000, 2400, …, 4800} are applied. For MRP planning, the used safety stock parameter *SS* also corresponds to the initial stocking quantity, and for the RPS the *RP* parameter value is the initial stocking quantity. In total 36,192 (22,272 FOQ, 13,920 FOQ) different iterations for MRP and 5,568 for RPS are evaluated with the simulation model. Each one is replicated 10 times per iteration, to account for the stochastic influence during simulation, resulting in 417,600 individual replications. The representation of confidence intervals has been omitted, however, all mayor difference in costs are signification with confidence level of lower than 0.05. Confidence levels of representation are not included for clarity purposes.

4 NUMERICAL RESULTS

In this section, the stated research questions are answered using the results of the conducted simulation study. As stated in the introduction, we investigate in which situations standard MRP with its rolling horizon planning capability benefits from uncertain demand forecasts and what conditions lead to a better performance of RPS. The discussed cost results represent the overall costs per period computed by the sum of finished goods inventory (FGI), Work in Progress (WIP) and tardiness per unit. For FGI a costing factor of 1 is applied, for WIP 0.5 and for tardiness of 19. The relation of WIP and tardiness costs represents a target service level of 95 %. Inventory costs are twice of WIP as it is more costly to store end items.

4.1 Effects of Unsystematic Forecast Uncertainty

To answer RQ1 and discuss the effect of forecast uncertainty on MRP and RPS, Figure 2a shows the minimum costs with respect to α which are reached for MRP with *FOQ*, MRP with *FOP*, and *RPS* when the planning parameters are optimized for the medium shop load scenario.

In general, Figure 2a shows that a higher forecast uncertainty, which also implies higher final order amount uncertainty, leads to high costs for both methods MRP and RPS. Further, the results show that both lot sizing policies, i.e., FOP and FOQ perform very similar in situations without forecast bias. For very low α values, which imply a very low uncertainty for the final order amount, the application of demand forecast in MRP leads to higher costs. The reason is that applying forecast updates in MRP leads in some situations to additional orders, however, the number of updates implies only low final order amount disturbances and can better be handled with RPS. The detailed analysis of safety stock *SS* for MRP shows that both FOP and FOQ react with a higher safety stock on a higher forecast uncertainty (see Figure 2b). Note that for all uncertainty settings the *PLT*=2 was optimal in MRP. Related to RPS, higher α values, which lead to higher fluctuations in final order amounts, imply higher optimal *RP* values (see Figure 2b), which is in line with inventory control literature where the optimal reorder point should be the maximum of demand during the replenishment time. An interesting finding is, that higher forecast uncertainty (and final order amount fluctuations) lead for MRP and RPS to higher production lot sizes. Specifically, the finding that FOQ and RPS have the same optimal lot size for an unbiased forecast value between 0.025 and 0.175 is interesting (see Figure 2c). In general, a higher lot size, leads to an overall higher inventory level and to a lower utilization. The higher inventory level helps to avoid a stock out situation and the lower utilization enables shorter lead times and a more flexible production process. Additionally, the finding confirms the intuitive expectation, that the MRP FOQ lot size and the reorder point lot size are very similar.

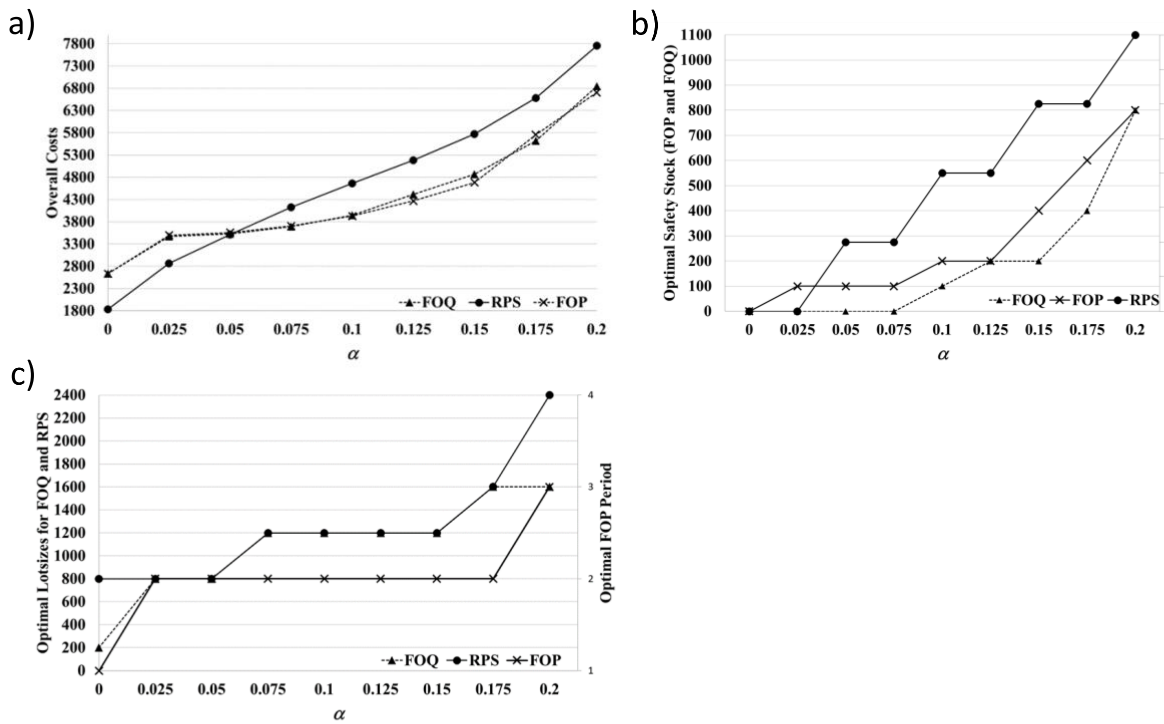

Figure 2: Results unbiased forecast error: comparison a) cost, b) safety stock vs. reorder point, c) lot size.

4.2 Overbooking and Underbooking Comparison

To answer RQ2 and RQ3 and evaluate the effect of overbooking and underbooking on the optimal planning method, Figure 3 shows the minimum costs for MRP (with FOP and FOQ) and RPS for medium shop load and α=0.05 as well as α=0.1 with respect to the tested systematic forecast bias value β.

Since the modeling assumptions concerning forecast bias lead to higher long-term forecasts for overbooking and lower long-term forecast for underbooking, the demand forecast update uncertainty σ_ε is influenced accordingly, i.e., higher β implies higher uncertainty for overbooking and lower uncertainty for underbooking, compare to Equation (3). Related to RQ2, the results show that overbooking with high forecast uncertainty and forecast bias leads to the highest cost. For underbooking, i.e., the forecasts are too low, RPS works better when forecast uncertainty α is low (see Figure 3a) but RPS performs worse in all other situations (see Figure 3b–d). In the situation underbooking and low α (see Figure 3a) FOQ works better than FOP for moderate to high systematic forecast bias. In all scenarios with high α, MRP-FOP and MRP-FOQ perform very similar. In the underbooking situation for low α and high forecast bias, we see that MRP-FOQ performance is superior to MRP-FOP performance. The study shows for scenarios with overbooking, always MRP outperforms RPS. Contrary to MRP, RPS ignores the forecast information, but its performance is strongly dependent on the demand uncertainty. This implies in the underbooking case for higher β values (these lead to lower long term forecasts) the final order amount fluctuation is lower. Therefore, RPS leads to lower costs for higher β values and the opposite holds for overbooking.

4.3 Detailed Analysis of Underbooking Behavior with Low Forecast Uncertainty

Table 2 shows the overall costs and the optimal planning parameters for MRP and RPS method for α=0.05 for three different utilization values (i.e., low, medium, and high). The Δ sign indicates the delta of costs in percentage calculating $\Delta = 100 * (cost_{RPS} - cost_{MRP})/cost_{MRP}$. The study shows that for low forecast uncertainty and a low utilization level, RPS performs better than the MRP method. In most other scenarios MRP outperforms RPS (see Table 3 in Section 4.4). The summarizing Table 2 shows that in situations with high-capacity buffer (i.e., low utilization level) and low demand variations, RPS is more efficient than MRP. In this situation MRP cannot benefit from using the demand forecast information, especially as it is biased and too low values are forecasted, i.e., a higher backorder risk occurs.

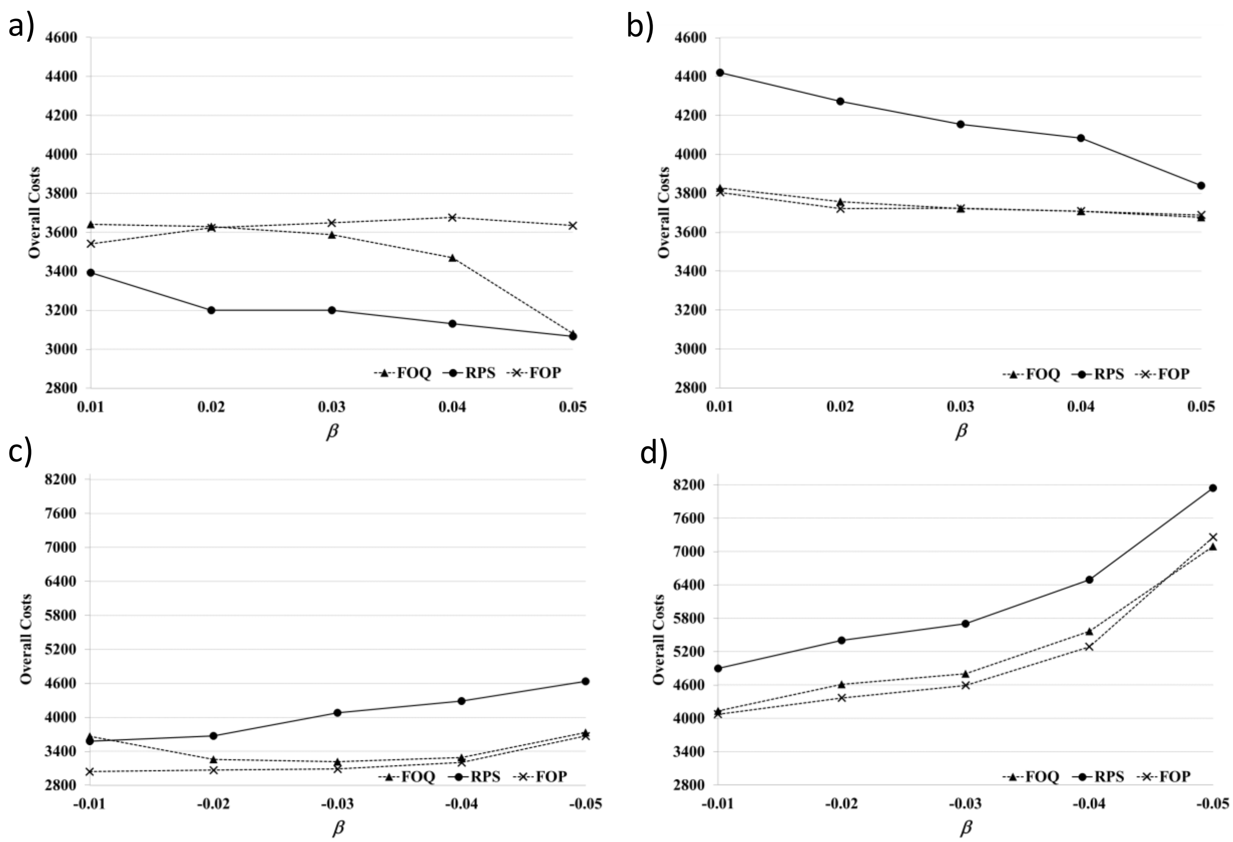

Figure 3: Overall costs for: underbooking a) α=0.05, b) α=0.1, and overbooking c) α=0.05, d) α=0.1.

The lot size for RPS is quite stable for the RPS system whereas the reorder point increases with respect to the planned utilization level. Analyzing the parameter optimization results, we see that the optimal lead time for MRP is almost constant for all scenarios. Note that this finding is limited by the very streamlined production system with one BOM-level. For MRP the results show that in 11 out of 18 scenarios FOP is superior to FOQ. In general, the investigation shows that for low and medium utilization levels in the underbooking scenario with low forecast uncertainty RPS is superior compared to MRP. For high utilization values results do not confirm this finding.

4.4 Overall Cost Comparison

To discuss the sensitivity of the results, Table 3 presents the overall costs of MRP and RPS with respect to different levels of the forecast uncertainty α, different levels of forecast bias β, and three different utilization levels. The Δ sign represents as defined in Section 4.3 the cost delta in % comparing MRP and RPS costs. The first two columns (MRP/RPS/Δ) stand for the underbooking scenario ($\beta > 0$) whereas the third and fourth column show the results of the overbooking ($\beta < 0$) scenario.

The results show that for most investigated scenarios RPS is only superior in the underbooking scenarios ($\beta > 0$), when forecast uncertainty α is low and utilization levels are low or moderate. This is also in line with the findings discussed in Section 4.3. In all other situations, MRP and the use of forecast information leads to better overall costs than using RPS as planning method. For these scenarios, the integration of forecast information leads to a superior setting compared to the RPS system where production orders are issued based on the historical order amounts and the predefined static reorder point. When comparing the results of column one and three (low α) with column two and four (high α), results show that higher forecast uncertainty leads to higher costs and, specifically for low and medium utilization, to a higher cost reduction potential when MRP is applied. A managerial insight is that even uncertain and biased forecasts can often to be exploited by MRP, specifically on high uncertainty of final order amounts.

Table 2: Optimal costs and optimal planning parameters for underbooking and α=0.05

		RPS			MRP					Cost Δ % RPS/MRP
	low util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3034	2000	800	3451	FOQ	800	2	0	-12.1
	0.01	2953	2000	800	3575	FOQ	800	2	0	-17.4
	0.02	2878	2000	800	3664	FOP	2	2	100	-21.5
	0.03	2887	2000	800	3463	FOQ	800	2	0	-16.6
	0.04	2863	2000	800	3402	FOQ	800	2	100	-15.8
	0.05	2842	2000	800	3059	FOQ	800	2	0	-7.1
		RPS			MRP					Cost Δ % RPS/MRP
	med util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3512	2400	800	3526	FOQ	800	2	0	-0.4
	0.01	3393	2000	800	3541	FOP	2	2	100	-4.2
	0.02	3201	2000	800	3623	FOP	2	2	100	-11.6
	0.03	3200	2000	800	3589	FOQ	800	2	100	-10.8
	0.04	3130	2000	800	3469	FOQ	800	2	200	-9.8
	0.05	3065	2000	800	3079	FOQ	800	2	100	-0.5
		RPS			MRP					Cost Δ % RPS/MRP
	high util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3885	2400	1200	3522	FOP	2	2	100	10.3
	0.01	3824	2400	800	3514	FOP	2	2	100	8.8
	0.02	3647	2400	800	3580	FOP	2	2	100	1.9
	0.03	3530	2400	800	3618	FOQ	1200	2	0	-2.4
	0.04	3482	2400	800	3606	FOQ	1200	2	100	-3.4
	0.05	3447	2400	800	3203	FOQ	800	2	100	7.6

5 CONCLUSION

This article describes a performance comparison of standard MRP and RPS planning methods by the means of simulation. A simulation model to study a multi-item single stage production system is developed and the differences in the performance of MRP and RPS are measured analyzing overall costs which are the sum of inventory and tardiness costs. For different levels of the forecast uncertainty, different levels of systematic forecast bias (i.e., overbooking and underbooking), and three different utilization levels, the optimal planning parameters for MRP and RPS are identified by a simulation study. A full factorial experiment design is used to find the superior planning parameter setting and discuss the optimal overall costs. The study shows that for most scenarios MRP outperforms RPS, i.e., the integration of forecast information leads to a planning advantage even if it is biased. Only in the underbooking scenarios when forecast uncertainty is low, RPS leads to better results than MRP. In these mentioned scenarios, the integration of uncertain and biased forecast information provides too less value for MRP, and the low uncertainty of final order amounts leads to advantages of the RPS method as in these situations low reorder points are sufficient. For the scenarios without forecast bias we see that the higher the forecast uncertainty, the higher are the overall costs and the higher the inventory level that is needed. For comparing overbooking and underbooking, the results confirm that in general overbooking is more beneficial for MRP and the implied higher risk of shortages in underbooking partially favors RPS. For overbooking, the cost advantages comparing MRP with RPS reach from 8 % to 30 %. For unbiased scenarios we find that RPS only performs better if the uncertainty of final order amounts is very low, in all other unbiased scenarios MRP outperforms RPS. Overall, the results show that there is no significant difference between the two tested MRP lot sizing policies FOP and FOQ for the scenarios without forecast bias. The parameter optimization results bring us to the finding that the best reorder point is always higher than the identified safety stock in MRP. Another interesting finding is that higher forecast uncertainty also leads to higher lot sizes. The higher lot sizes cause lower production system utilization and, therefore, increase flexibility for the demand uncertainty which has a positive effect on the production system performance. In further research activities, forecast evolution could be extended with shifting demand feature and for this also optimal parameter setting for MRP and RPS should be tested. The investigation of a forecast correction method in the scenario with biased forecast information and its costs performance for more complex production systems also need further investigation.

Table 3: Comprehensive overall cost comparison.

low util		α=0.05			α =0.1		
		MRP	RPS	Δ %	MRP	RPS	Δ
β	0	3451	3034	-12.1	3765	4082	8.4
	0.01	3575	2953	-17.4	3719	3785	1.8
	0.02	3664	2878	-21.5	3661	3652	-0.2
	0.03	3463	2887	-16.6	3679	3600	-2.1
	0.04	3402	2863	-15.8	3696	3532	-4.4
	0.05	3059	2842	-7.1	3675	3378	-8.1
med util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3526	3512	-0.4	3928	4665	18.8
	0.01	3541	3393	-4.2	3804	4419	16.2
	0.02	3623	3201	-11.6	3721	4273	14.8
	0.03	3589	3200	-10.8	3721	4155	11.7
	0.04	3469	3130	-9.8	3707	4084	10.2
	0.05	3079	3065	-0.5	3677	3840	4.4
high util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3522	3885	10.3	4463	5163	15.7
	0.01	3514	3824	8.8	4144	4695	13.3
	0.02	3581	3647	1.9	3937	4553	15.6
	0.03	3618	3530	-2.4	3859	4460	15.6
	0.04	3606	3482	-3.4	3744	4325	15.5
	0.05	3203	3447	7.6	3690	4189	13.5

low util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3451	3034	-12.1	3765	4082	8.4
	-0.01	2650	3100	17.0	3823	4453	16.5
	-0.02	2793	3259	16.7	3917	4739	21.0
	-0.03	2902	3516	21.1	4019	4972	23.7
	-0.04	3016	3674	21.8	4360	5653	29.7
	-0.05	3145	4033	28.2	5181	6692	29.2
med util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3526	3512	-0.4	3928	4665	18.8
	-0.01	3041	3576	17.6	4075	4897	20.2
	-0.02	3068	3672	19.7	4370	5403	23.6
	-0.03	3087	4083	32.2	4595	5703	24.1
	-0.04	3203	4286	33.8	5288	6496	22.8
	-0.05	3669	4636	26.3	7097	8145	14.8
high util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3522	3885	10.3	4463	5163	15.7
	-0.01	3552	3961	11.5	4760	5491	15.4
	-0.02	3621	4093	13.0	5344	6023	12.7
	-0.03	3710	4309	16.1	5700	6337	11.2
	-0.04	3887	4550	17.1	6683	7458	11.6
	-0.05	4277	5078	18.7	8509	9478	11.4

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REFERENCES

Altendorfer, K. 2019. "Effect of limited Capacity on Optimal Planning Parameters for a Multi-item Production System with Setup Times and Advance Demand Information". *International Journal of Production Research* 57:1892–1913.

Altendorfer, K., and T. Felberbauer. 2023. "Forecast and Production Order Accuracy for Stochastic Forecast Updates with Demand Shifting and Forecast Bias Correction". *Simulation Modelling Practice and Theory* 125:102740.

Altendorfer, K., T. Felberbauer, and H. Jodlbauer. 2016. "Effects of Forecast Errors on Optimal Utilisation in Aggregate Production Planning with Stochastic Customer Demand". *International Journal of Production Research* 54:3718–3735.

Altendorfer, K., and S. Minner. 2014. "A Comparison of Make-to-Stock and Make-to-Order in Multi-Product Manufacturing Systems with Variable Due Dates". *IIE Transactions* 46:197–212.

Axsäter, S. 2007. *Inventory Control. New York, NY:* Springer Science & Business Media.

Benjaafar, S., W.L. Cooper, and S. Mardan. 2011. "Production-Inventory Systems with Imperfect Advance Demand Information and Updating". *Naval Research Logistics (NRL)* 58:88–106.

Enns, S.T. 2001. "MRP Performance Effects Due to Lot Size and Planned Lead Time Settings". *International Journal of Production Research* 39:461–480.

Enns, S.T. 2002. "MRP Performance Effects Due to Forecast Bias and Demand Uncertainty". *European Journal of Operational Research* 138:87–102.

Heath, D.C., and P.L. Jackson. 1994. "Modeling the Evolution of Demand Forecasts with Application to Safety Stock Analysis in Production/Distribution Systems". *IIE Transactions* 26:17–30.

Ho, C.-J., and T.C. Ireland. 1998. "Correlating MRP System Nervousness with Forecast Errors". *International Journal of Production Research* 36:2285–2299.

Hopp, W.J., and M.L. Spearman. 2011. *Factory Physics*. Waveland: Long Grove, IL.

Juan, A.A., J. Faulin, S.E. Grasman, M. Rabe, and G. Figueira. 2015. "A Review of Simheuristics: Extending Metaheuristics to Deal with Stochastic Combinatorial Optimization Problems". *Operations Research Perspectives* 2:62–72.

Li, Q., and S.M. Disney. 2017. "Revisiting Rescheduling: MRP Nervousness and the Bullwhip Effect". *International Journal of Production Research* 55:1992–2012.

Norouzi, A., and R. Uzsoy. 2014. "Modeling the Evolution of Dependency Between Demands, with Application to Inventory Planning". *IIE Transactions* 46:55–66.

Seiringer, W., K. Altendorfer, J. Castaneda, L. Gayan, and A.A. Juan. 2022a. "Potential of Simulation Effort Reduction by Intelligent Simulation Budget Management for Multi-Item and Multi-Stage Production Systems". In *Proceedings of the 2022 Winter Simulation Conference*, edited by B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, 1864–1875. Piscataway, NJ: IEEE.

Seiringer, W., J. Castaneda, K. Altendorfer, J. Panadero, and A.A. Juan. 2022b. "Applying Simheuristics to Minimize Overall Costs of an MRP Planned Production System." *Algorithms* 15:40.

Silver, E.A., D.F. Pyke, and R. Peterson. 1998. *Inventory Management and Production Planning and Scheduling*, 3rd ed. New York, Chichester: Wiley.

Tempelmeier, H. 2011. *Inventory Management in Supply Networks: Problems, Models, Solutions. Norderstedt, Germany:* Books on Demand.

Wijngaard, J. 2004. "The Effect of Foreknowledge of Demand in Case of a Restricted Capacity: The Single-Stage, Single-Product Case". *European Journal of Operational Research* 159:95–109.

Zeiml, S., K. Altendorfer, T. Felberbauer, and J. Nurgazina. 2019. "Simulation Based Forecast Data Generation and Evaluation of Forecast Error Measures". In *Proceedings of the 2019 Winter Simulation Conference*, edited by N. Mustafee, K.-H. G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, 2119–2130. Piscataway, NJ: IEEE.

AUTHOR BIOGRAPHIES

WOLFGANG SEIRINGER is Research Associate in the field of Operations Management at the University of Applied Sciences Upper Austria. His research interests are discrete event simulation, hierarchical production planning, information uncertainty and supply chain optimization. His email address is wolfgang.seiringer@fh-steyr.at.

KLAUS ALTENDORFER is Professor in the field of Operations Management at the University of Applied Sciences Upper Austria. He received his PhD degree in Logistics and Operations Management and has research experience in simulation of production systems, stochastic inventory models, and production planning and control. His e-mail address is klaus.altendorfer@fh-steyr.at.

THOMAS FELBERBAUER is academic director of the study program Smart Engineering at the St. Pölten University of Applied Sciences (Austria). He works as a professor in the field of production planning and simulation at the Department Media and Digital Technologies. He received his PhD degree developing solution methods for stochastic project management. His email address is thomas.felberbauer@fhstp.ac.at.