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SIMULATION ANALYSIS OF A MULTI-ITEM MRP SYSTEM BASED ON FACTORIAL DESIGN

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ABSTRACT

MRP (Material Requirements Planning) has been widely used as a production scheduling system in many companies for at least the past twenty-five years. However, it is a deterministic planning tool, and therefore its ability as an effective planning tool when there is a high degree of uncertainty is questionable. In this study, we develop a multi-item MRP simulation model and design experiments to determine the effects of factors such as forecast errors, process variability and updating on key performance measures. The analysis of variance (ANOVA) results show that these factors affect the inventory and fill rate significantly.

1 INTRODUCTION

MRP is one of the earliest computerized production scheduling approaches. Although it started slowly, MRP got an extensive boost in 1972 because the American Production and Inventory Control Society (APICS) launched its “MRP Crusade” to promote its use (Hopp and Spearman 2008). MRP is still regarded as one of the most widely used systems for production scheduling (Mohan and Ritzman 1998). However, there is a conflict between MRP’s deterministic nature and the uncertainty seen in most operations which makes an MRP planning system vulnerable to the effects of uncertainty. This paper is designed to investigate the MRP effects on key performance measures due to forecast errors, process variability and updating frequency in the system.

MRP’s deterministic calculation is based on the forecast demand, and it is well known that the actual demand cannot be predicted exactly. MRP determines the start times of the jobs by offsetting the due dates of the jobs by fixed planned lead times, which is rarely achieved in practice due to the uncertainty in the system, e.g. process variability. Also a key determinant of the effectiveness of an MRP system is the updating frequency. If we update too frequently, the shop is busy constantly changing planned order releases. If we update too infrequently, we can end up with old plans that are often out of date. Hence, in this paper, we chose forecast errors, process variability and updating frequency as the factors to be investigated in the MRP system.

We use simulation to estimate the performance of an MRP system under different operating conditions. Simulation is a commonly used tool to examine complex manufacturing systems.

Lee and Adam (1986) conducted a simulation study to examine two dimensions of forecast error - standard deviation and bias. They found that standard deviation is relatively less important in terms of the magnitude of the total cost impact, which includes inventory carrying cost, setup cost and enditem shortage cost. Their results suggest that higher forecast error level may not result in higher total cost, which seems to contradict what we intuitively believe.

Wemmerlov (1986) conducted a simulation study which was observed under three conditions: no demand uncertainty, demand uncertainty present but no safety stocks are available, and demand uncertainty present with safety stocks maintained to counter its effects. The results showed that stockouts, larger inventories, and more orders occurred simultaneously when demand uncertainty was introduced in the system. Service levels decreased and inventory levels increased when forecast error became larger. In addition, the experiments showed that introduction of safety stocks to counter the effect of the forecast errors leads to reduction of shortages, but increases the expense of additional inventories and orders.

Enns (2001) conducted a series of experiments to investigate the effects of forecast bias and demand uncertainty in a batch production environment. An inflated planned lead time and safety stock are used to compensate for forecast error. The analysis of performance focused on the MPS due dates and customer delivery requirements. Forecast bias and demand uncertainty were shown to have a bigger impact on customer delivery service levels than on master scheduling performance. Enns’ (2001) results also showed that increasing planned lead times and adding safety stock are both effective in improving delivery performance. If demand uncertainty dominates completion time variability, safety stock will meet delivery objectives with smaller finished goods inventory.

Grasso and Taylor (1984) employed a MRP/Production simulator to examine the impact of operation policies on the total cost of the MRP system given supply uncertainty resulting from timing factors, such as the amount of lead time variability, the amount of safety stock or safety lead time, the lot-size rule, the holding cost and lateness penalty. Their results showed that the total cost of the MRP system is affected by all the factors.

Ho and Ireland (1998) conducted a simulation experiment to examine the impact of forecasting errors on the scheduling instability in a MRP system. They found that forecasting errors might not cause a higher degree of scheduling instability, which can be mitigated by using an appropriate lot-sizing rule. They suggested that applying EOQ and lot-for-lot (LFL) creates a significantly more nervous MRP system than applying part-period balancing (PPB) and the Silver-Meal (SM) approach. They also found that the selection of an appropriate lot-sizing rule can be effective in dealing with forecast errors when lead time tends to fluctuate.

Yeung, Wong, and Ma (1998) reviewed important parameters which have an impact on the effectiveness of MRP systems. They classified papers in the literature into seven groups based on their impact on MRP performance: 1) MPS frozen interval; 2) MPS replanning frequency; 3) MPS planning horizon; 4) Product structure; 5) Forecast error; 6) Safety stock; 7) Lot-sizing rules.

This paper is designed to investigate the important effects on inventory and fill rate levels due to forecast errors, process variability and updating frequency. The simulation experiments are developed via factorial design. ANOVA results are analyzed to show the effects of the main factors and their interactions.

2 SIMULATION MODELING OF AN MRP SYSTEM

Basically the MRP system procedure consists of three main steps. The first step is to determine net requirements by deducting on-hand inventory and any scheduled receipts from the gross requirements. The next step is to divide the net requirements into appropriate lot sizes to form jobs. The last step is to determine start times of the jobs by offsetting the due dates of the jobs by planned lead times.

In our MRP simulation model, three components are included.

In the first component, we update the inventory position based on forecast demand for a planning time horizon. Then we calculate the net requirement for each product deterministically based on the updated inventory. We then calculate the planned order receipts and determine the planned order release by taking into consideration the production lead times (see Figure 1).

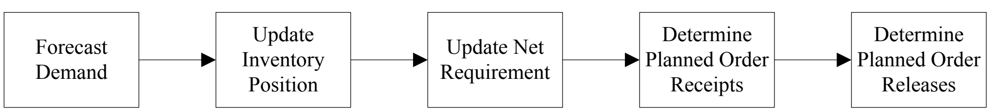

Figure 1: planning procedure in MRP simulation model

Table 1 shows the notations used in the procedure calculation.

Table 1: Notations

Notations	
$D_i(t)$	forecast demand for product *i* in period *t*
$IP_i(t)$	projected inventory position for product *i* in period *t*
$D_i(0)$	demands due before the first period for product *i*
$w_i(t)$	work orders for product *i* in period *t*
$NR_i(t)$	net requirements for product *i* in period *t*
$PO_i(t)$	planned order receipts for product *i* in period *t*
$PW_i(t)$	planned work orders for product *i* in period *t*

Consider a set of forecast demand, denoted as $D_i(t)$, $t = 0, \ldots, n$, where $D_i(t)$ equals the forecast demand for product *i* in period *t*. Note that $D_i(0)$ is the sum of the demands due before the first period. The period in our model is one day and the default planning horizon is four weeks.

The projected inventory position in period t, $IP_i(t)$ is computed as:

$$IP_i(t) = IP_i(t-1) - D_i(t)$$
$$IP_i(0) = w_i(0) - D_i(0)$$

$w_i(0)$ is the current on-hand inventory.

The next step is to get the net requirement for each product in each period, which is the demand beyond what the on-hand inventory and the scheduled receipts can cover. $NR_i(t)$ is calculated as

$$NR_i(t) = \min\left\{D_i(t), \max\left\{0, -IP_i(t)\right\}\right\}$$

This formula makes the net requirement equal to the magnitude of the first negative projected inventory or the demand for the period, whichever is smaller.

Then we compute the planned order receipts $PO_i(t)$. In our model we use reorder quantity Q as the lot size. Thus the planned order release is an integer multiple of Q.

The last step is to assign the planned work orders. We determine the planned work orders by taking into consideration the production lead times. We calculate the planned lead time l by dividing reorder point by average daily demand. Then, the planned work orders, $PW_i(t)$ are given by

$$PW_i(t) = PO_i(t+l)$$

The second part of the MRP model triggers production based on the order release plan schedule, which is illustrated in Figure 2. First, we check the production plan each day to see if there are any planned order releases for the products. If so, we trigger a production and update the inventory level.

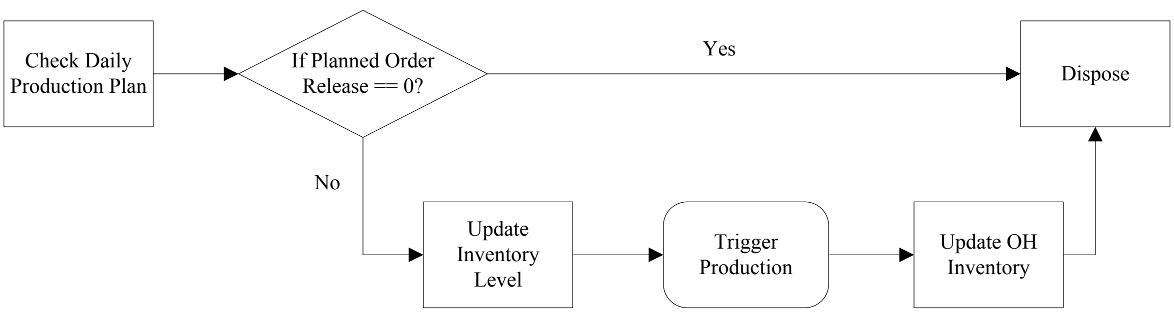

Figure 2: Production process in MRP simulation model

The third part of the MRP system is about examining the actual order demand to update the inventory level, which is illustrated in Figure 3. When a demand is realized, we update the inventory level and compare the inventory level with the reorder point. If the inventory level is greater than reorder point, the order is filled directly from the stock. Otherwise, it becomes backorder.

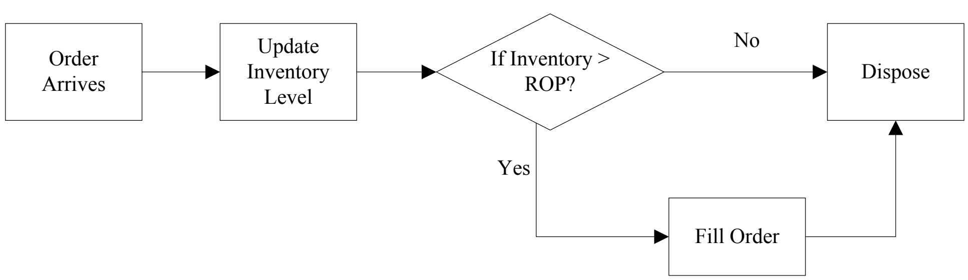

Figure 3: Order demand procedure in MRP simulation model

3 EXPERIMENTAL DESIGN

We now evaluate the effects of demand uncertainty, forecast bias, process variability and updating frequency on inventory level and fill rate. Factorial design is used to develop simulation experiments for a multi-item MRP system to determine the effects of the above factors and their interactions. Table 2 shows the levels of the factors we examined.

Table 2: Levels of factors

Factors	Levels
Process Variability	moderate, none
Demand Uncertainty	moderate, none
Forecast Bias	base, underestimated, overestimated
Updating Frequency	once a week, once in two weeks

The overall environment for the multi-item system considers 23 parts manufactured in a single-machine flowshop. We consider two levels of process variability - moderate variability and zero variability. In the scenario with moderate process variability, the process time is exponentially distributed, while in the scenario without process variability, the process time is constant. The forecast error is the combination of both forecast bias (the difference between the mean of the demand distribution and the forecast for a given point in time) and demand uncertainty (the fluctuation in demand), as discussed in Enns (2002). We consider three levels of forecast bias - base demand, overestimated demand and underestimated demand scenarios. In the base demand scenario, the mean of actual order demand per period is equal to the forecast demand. In the overestimated demand scenario, the forecast demand is overestimated by 20% for each product, which means that the actual mean demand for each product is 20% lower than the forecast demand. In the underestimated demand scenario, the forecast demand is underestimated by 20% for each product, which means that the actual mean demand for each product is 20% higher than the forecast demand. We examine two levels of demand uncertainty as well, which are moderate demand uncertainty and no demand uncertainty. In the scenario with moderate demand uncertainty, the number of actual orders per period follows a Poisson distribution, and the order size is normally distributed. In the scenario with no demand uncertainty, the number of orders per period and the order size are constant. Updating frequency is another factor to be examined. We consider two levels of updating frequency in the experiments – once a week and once in two weeks. In other words, the MRP plan is updated once or twice a week. The simulation experiments are conducted based on four different factors shown in Table 2.

A full factorial design is employed to examine the effects of the above factors and their interactions under the MRP system. All possible combinations of factor setting are examined. A total of 2*3*2*2 = 24 scenarios (two process variability, three forecast biases, two demand uncertainty, and two updating frequencies) are examined.

Fill rate and inventory are the two output performance measures used to examine the MRP performance under different scenarios in our study. Fill rate is related to customer satisfaction. The higher the fill rate, the greater the customer satisfaction is. We consider two kinds of fill rate - fill rate based on time and fill rate based on units. Fill rate based on time is the fraction of time the system does not have backorders, while fill rate based on units is the fraction of demand (based on units) that will be filled from stock. Both fill rates represent a reasonable definition of the customer service level. An MRP system aims to achieve a high fill rate, while keeping a relatively low inventory level because units in inventory incur a holding cost. Thus, inventory is another important measure in our study. We use the aggregate value of fill rate and inventory for comparison under different scenarios, which is a weighted average over average demand rate for each product.

We set each of the simulation scenarios run for ten independent replications. The warm up period for each simulation run is one year and the run length is ten years.

4 RESULTS OF EXPERIMENTATION

After we run 10 replications of each of the 24 simulation experiment scenarios, 240 response values are obtained for each performance measure (i.e. aggregate average inventory, aggregate fill rate based on time and aggregate fill rate based on units). The output performance measures are given in Table 3, which are the average values from 10 replications. Examining experimental data visually reveals some intuitive results. We can see that the forecast bias affects the performance measures consistently, i.e. underestimated forecast can decrease the average inventory and fill rate, while overestimated forecast can increase the average inventory and fill rate, when other three factors keep constant. The similar results also can be obtained within the levels of process variability and demand uncertainty, i.e. no process variability and no demand uncertainty can improve the fill rate compared to moderate variability.

Table 3: Summary of output performance measures

Scenario	Updating Frequency	Process Variability	Demand Uncertainty	Forecast Bias	Average Inventory	Fill Rate Based on Time	Fill Rate Base on Units
1	once a week	moderate	moderate	base	34161	81.0%	91.4%

2	once a week	moderate	moderate	underestimated	26772	46.4%	79.8%
3	once a week	moderate	moderate	overestimated	39513	94.4%	97.4%
4	once a week	moderate	none	base	33920	82.9%	93.6%
5	once a week	moderate	none	underestimated	26561	50.1%	83.0%
6	once a week	moderate	none	overestimated	39523	96.4%	99.8%
7	once a week	none	moderate	base	34968	92.4%	92.6%
8	once a week	none	moderate	underestimated	28182	73.1%	82.4%
9	once a week	none	moderate	overestimated	39709	98.6%	97.6%
10	once a week	none	none	base	35268	95.2%	95.6%
11	once a week	none	none	underestimated	28128	76.3%	85.8%
12	once a week	none	none	overestimated	39453	99.9%	99.8%
13	once in two wks	moderate	moderate	base	33617	79.2%	89.6%
14	once in two wks	moderate	moderate	underestimated	18810	41.8%	64.8%
15	once in two wks	moderate	moderate	overestimated	43367	96.5%	98.4%
16	once in two wks	moderate	none	base	34134	82.9%	94.1%
17	once in two wks	moderate	none	underestimated	20081	43.6%	70.1%
18	once in two wks	moderate	none	overestimated	43027	97.5%	100.0%
19	once in two wks	none	moderate	base	34688	91.3%	91.0%
20	once in two wks	none	moderate	underestimated	20829	60.3%	68.2%
21	once in two wks	none	moderate	overestimated	43431	99.2%	98.5%
22	once in two wks	none	none	base	35613	95.7%	96.1%
23	once in two wks	none	none	underestimated	22911	67.1%	76.0%
24	once in two wks	none	none	overestimated	43025	100.0%	100.0%

In order to further examine the performance effects of all the factors and their interactions rather than visual observations, the results are analyzed using ANOVA which can evaluate the significance of several different factors and their potential interactions. We completed ANOVA in the statistical software MINITAB at 95% confidence level. The ANOVA results for the three performance measures (i.e. aggregate inventory, aggregate fill rate based on time and aggregate fill rate based on units) are presented in Tables 4-6. Because the ANOVA assumptions are met, we can interpret our results based on ANOVA results. The ANOVA assumptions are that residuals are normally distributed and have a mean of zero and constant variance. The *F*-test is applied to compare variance. The bigger the *F* value, the more likely it is that the factor is significant. We arrange the ANOVA Tables 4-6 according to descending order of *F* values to determine the most significant factors visually. The *P* values in last columns in Tables 4-6 indicate whether or not the main and interaction factor effects are significant. If the *P* value is smaller than 0.05, the effect is significant. Otherwise, it is not. The rows of all significant factors ($P<0.05$) are shown in bold in each table. From the ANOVA tables, we find the following:

- *Main effects of the factors*: The main effect of a factor is the average change in the output due to the factor shifting from one level to other levels, while holding all other factors constant. *P* values for all the factors (i.e. updating frequency, process variability, demand uncertainty and forecast bias) are less than 0.05, which means that the factors all significantly affect all the performance measures (i.e. inventory, fill rate based on time and fill rate based on units).
- *Two-way interactions*: Two-way interactions involve the interaction of two variables and indicate that the effect of one factor is different at different levels of the other factor. All the two-way interactions, except the interaction between process variability and demand uncertainty, are significant for the inventory performance. All the two-way interactions, with the exclusion of process variability*demand uncertainty and updating frequency*demand uncertainty, are significant for the fill rate based on time. All the two-way interactions significantly affect the fill rate based on units.
- *Three-way interactions*: Three-way interaction effect means that there is a two-way interaction that varies across levels of a third variable. Two of the four three-way interactions are significant to inventory, which are Updating Fre-

quency*Process Variability*Forecast Bias and Updating Frequency*Demand Uncertainty*Forecast Bias. Only one three-way interaction significantly affects the fill rate based on time, which is Updating Frequency*Process Variability*Forecast Bias. Three of the four three-way interactions are significant to fill rate based on units, only excluding Updating Frequency*Process Variability*Demand Uncertainty.

- *Four-way interactions*: Four-way interactions occur when three-way interactions differ as a function of the level of a fourth variable. There is only one performance measure (i.e. fill rate based on unit) affected by four-way interaction significantly.

Table 4: ANOVA results for aggregate inventory

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Forecast Bias	**2**	**12216651884**	**12216651884**	**6108325942**	**22206.58**	**0**
Updating Frequency*Forecast Bias	**2**	**1114124243**	**1114124243**	**557062121**	**2025.18**	**0**
Process Variability	**1**	**67413963**	**67413963**	**67413963**	**245.08**	**0**
Updating Frequency	**1**	**66418320**	**66418320**	**66418320**	**241.46**	**0**
Process Variability*Forecast Bias	**2**	**36854690**	**36854690**	**18427345**	**66.99**	**0**
Updating Frequency*Demand Uncertainty	**1**	**8442883**	**8442883**	**8442883**	**30.69**	**0**
Demand Uncertainty	**1**	**5391553**	**5391553**	**5391553**	**19.6**	**0**
Updating Frequency*Demand Uncertainty*Forecast Bias	**2**	**10626446**	**10626446**	**5313223**	**19.32**	**0**
Demand Uncertainty*Forecast Bias	**2**	**10572378**	**10572378**	**5286189**	**19.22**	**0**
Updating Frequency*Process Variability	**1**	**2020019**	**2020019**	**2020019**	**7.34**	**0.007**
Updating Frequency*Process Variability*Forecast Bias	**2**	**2560698**	**2560698**	**1280349**	**4.65**	**0.01**
Process Variability*Demand Uncertainty	1	1050073	1050073	1050073	3.82	0.052
Process Variability*Demand Uncertainty*Forecast Bias	2	1385623	1385623	692811	2.52	0.083
Updating Frequency*Process Variability*Demand Uncertainty	1	217909	217909	217909	0.79	0.374
Updating Frequency*Process Variability *Demand Uncertainty*Forecast Bias	2	392629	392629	196315	0.71	0.491
Error	216	59414760	59414760	275068		
Total	239	13603538072				

Table 5: ANOVA results for aggregate fill rate based on time

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Forecast Bias	**2**	**7.07904**	**7.07904**	**3.53952**	**6373.19**	**0**
Process Variability	**1**	**1.01883**	**1.01883**	**1.01883**	**1834.48**	**0**
Process Variability*Forecast Bias	**2**	**0.42476**	**0.42476**	**0.21238**	**382.41**	**0**
Updating Frequency*Forecast Bias	**2**	**0.09797**	**0.09797**	**0.04898**	**88.2**	**0**
Demand Uncertainty	**1**	**0.04685**	**0.04685**	**0.04685**	**84.35**	**0**
Updating Frequency	**1**	**0.04153**	**0.04153**	**0.04153**	**74.78**	**0**
Updating Frequency*Process Variability	**1**	**0.00603**	**0.00603**	**0.00603**	**10.86**	**0.001**
Updating Frequency*Process Variability*Forecast Bias	**2**	**0.00978**	**0.00978**	**0.00489**	**8.8**	**0**
Demand Uncertainty*Forecast Bias	**2**	**0.00719**	**0.00719**	**0.00359**	**6.47**	**0.002**

Updating Frequency*Process Variability*Demand Uncertainty	1	0.00138	0.00138	0.00138	2.49	0.116
Updating Frequency*Process Variability *Demand Uncertainty*Forecast Bias	2	0.00254	0.00254	0.00127	2.29	0.104
Process Variability*Demand Uncertainty	1	0.00107	0.00107	0.00107	1.93	0.166
Process Variability*Demand Uncertainty*Forecast Bias	2	0.00182	0.00182	0.00091	1.64	0.196
Updating Frequency*Demand Uncertainty*Forecast Bias	2	0.0015	0.0015	0.00075	1.35	0.262
Updating Frequency*Demand Uncertainty	1	0.00052	0.00052	0.00052	0.95	0.332
Error	216	0.11996	0.11996	0.00056		
Total	239	8.86077				

Table 6: ANOVA results for aggregate fill rate based on units

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Forecast Bias	**2**	**2.20517**	**2.20517**	**1.10259**	**19051.22**	**0**
Updating Frequency*Forecast Bias	**2**	**0.226**	**0.226**	**0.113**	**1952.49**	**0**
Updating Frequency	**1**	**0.11281**	**0.11281**	**0.11281**	**1949.21**	**0**
Demand Uncertainty	**1**	**0.07366**	**0.07366**	**0.07366**	**1272.8**	**0**
Process Variability	**1**	**0.01964**	**0.01964**	**0.01964**	**339.35**	**0**
Process Variability*Forecast Bias	**2**	**0.01324**	**0.01324**	**0.00662**	**114.4**	**0**
Demand Uncertainty*Forecast Bias	**2**	**0.00903**	**0.00903**	**0.00452**	**78.04**	**0**
Updating Frequency*Demand Uncertainty	**1**	**0.00382**	**0.00382**	**0.00382**	**65.96**	**0**
Updating Frequency*Demand Uncertainty*Forecast Bias	**2**	**0.00442**	**0.00442**	**0.00221**	**38.2**	**0**
Updating Frequency*Process Variability	**1**	**0.00067**	**0.00067**	**0.00067**	**11.56**	**0.001**
Updating Frequency*Process Variability*Forecast Bias	**2**	**0.00119**	**0.00119**	**0.00059**	**10.27**	**0**
Process Variability*Demand Uncertainty	**1**	**0.00058**	**0.00058**	**0.00058**	**10.04**	**0.002**
Process Variability*Demand Uncertainty*Forecast Bias	**2**	**0.0006**	**0.0006**	**0.0003**	**5.19**	**0.006**
Updating Frequency*Process Variability *Demand Uncertainty*Forecast Bias	**2**	**0.0004**	**0.0004**	**0.0002**	**3.48**	**0.033**
Updating Frequency*Process Variability*Demand Uncertainty	1	0.00017	0.00017	0.00017	2.91	0.089
Error	216	0.0125	0.0125	0.00006		
Total	239	2.68391				

Overall, it can be concluded that MRP is not robust enough to deal with the process variability and forecast error, and the MRP performance is affected by updating frequency as well. Also the interactions of the factors have significant effects on MRP performance.

5 CONCLUSION

In this study, simulation experiments are conducted to examine the effects of forecast errors, process variability and updating frequency on MRP performance in terms of fill rate and inventory. We consider two levels of process variability (i.e. moderate and no), two levels of updating frequency (i.e. once a week and once every two weeks). The forecast error is combined by forecast bias and demand uncertainty. In our study, forecast bias has three levels (i.e. base, under-estimated, and over-estimated) and demand uncertainty has two levels (i.e. moderate and no). A full factorial design is employed in the simulation experiments to evaluate 24 scenarios. ANOVA is used to assess the significance of the factors and their interactions. The results show that all the factors and most of their interactions significantly affect the MRP performance in terms of fill rate and inventory.

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