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Impact of forecasting error on the performance of capacitated multi-item production systems

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Abstract

A computer model is built to simulate master production scheduling activities in a capacitated multi-item production system under demand uncertainty and a rolling time horizon. The output from the simulation is analyzed through statistical software. The results of the study show that forecasting errors have significant impacts on total cost, schedule instability and system service level, and the performance of forecasting errors is significantly influenced by some operational factors, such as capacity tightness and cost structure. Furthermore, the selection of the master production schedule freezing parameters is also significantly influenced by forecasting errors. The findings from this study can help managers optimize their production plans by selecting more reasonable forecasting methods and scheduling parameters, thus improving the performance of production systems.

Keywords: Forecasting error; Master production scheduling; Freezing parameters; Capacity constraint; Computer simulation

1. Introduction

Master production scheduling is a very important activity in manufacturing planning and control. The quality of the master production schedule (MPS) can significantly influence the total cost, schedule instability (SI) and service level (SL) of a production inventory system. The MPS drives the material requirements planning (MRP) system and provides the important link between forecasting, order entry and production planning activities on the one hand, and the detailed planning and scheduling of components and raw materials on the other. Frequent adjustments to the MPS can induce major changes in the detailed MRP schedules. These changes can lead to increases in production and inventory costs and deterioration in the level of customer service. This phenomenon is called 'schedule instability' or

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'MRP nervousness'. Maintaining a stable MPS in light of changing customer requirements, adjustments in sales forecasts and unforeseen supply or production problems is a difficult proposition for many firms (Sridharan, Berry, & Udayabhanu, 1988).

Several methods have been suggested to reduce SI in MRP systems. One frequently utilized method involves freezing the MPS (Blackburn, Kropp, & Millen, 1986, 1987). Several studies have proposed alternative ways of freezing MPS (Sridharan, Berry, & Udayabhanu, 1987; Sridharan et al., 1988) and have compared the effectiveness of freezing MPS against other methods (Kadipasaoglu & Sridharan, 1995; Sridharan & LaForge, 1990). Zhao and Lee (1993, 1996) examined the impact of different parameters for freezing MPS on total cost, SI and SL in multi-stage systems. Zhao and his co-workers (Zhao & Lam, 1997; Zhao, Goodale, & Lee, 1995; Zhao & Xie, 1998) also studied the impact of lot-sizing rules and forecasting models on the selection of MPS freezing parameters.

Although these studies address an important managerial issue in manufacturing planning and control and provide guidelines to help managers in their selection of MPS freezing parameters, they do not consider capacity constraints. Recently, Zhao, Xie, and Jiang (2001) studied the impact of MPS freezing parameters on the performance of multi-item, single-level production systems with a single resource constraint and deterministic demand. They found that some of the conclusions reached without considering capacity constraints could not be generalized to the more realistic capacitated situations. However, they did not examine the problem under demand uncertainty.

In reality, many companies do not know their future demands and have to rely on demand forecasts to make production planning decisions. They often use the same capacity to manufacture several products. Developing and maintaining an MPS under capacity constraints and demand uncertainty is far more challenging than doing so under no capacity constraints and deterministic demand. Both the capacity constraints and demand uncertainty may significantly influence the selection of the MPS freezing parameters.

This study is designed to investigate the performance of MPS freezing parameters in multi-item, single-level systems with a single resource constraint under demand uncertainty. Specifically, we will do the following:

1. Investigate the impact of freezing MPS on the performance of multi-item, single-level systems with a single resource constraint under demand uncertainty.
2. Evaluate the performance of the forecasting errors in multi-item, single-level systems with a single resource constraint under demand uncertainty.
3. Study the impact of forecasting errors on the selection of MPS freezing parameters under demand uncertainty.

In the following sections, we will first review the related literature and then discuss the research methodology and research hypotheses. We will then present our findings and, finally, we will conclude the paper with a summary of the research findings and suggest some possible future studies.

2. Related research

Because of the importance of maintaining a stable MPS and the difficulty of balancing the cost, SI and customer SL in making MPS freezing decisions, a number of researchers have investigated alternative methods of reducing SI. Blackburn et al. (1986, 1987) investigated five different strategies for reducing MRP nervousness and found that freezing the MPS is among the most effective strategies. Sridharan et al. (1987, 1988) developed a method to measure SI and studied the impact of MPS freezing on inventory costs and SI in single-level MPS systems under deterministic demand. Sridharan and Berry (1990b) presented a framework for designing MPS freezing methods under deterministic demand. They also compared the relative importance of the MPS freezing parameters in influencing the total cost and SI of the system. Lin and Krajewski (1992), Sridharan and Berry (1990a) and Sridharan and LaForge (1990, 1994) extended the studies by Sridharan et al. (1987, 1988) from the case of deterministic demand to the case of demand uncertainty by introducing forecasting errors into the system.

Zhao and Lee (1993, 1996) and Zhao and Lam (1997) extended the studies by Sridharan et al. (1987, 1988) from single-level systems to multi-level MRP systems and discovered that some findings in single-level systems cannot be generalized to multi-level systems. Zhao and Lee (1993) investigated the impact of forecasting errors on the performance of the MPS freezing parameters by simulating the forecasting process, as well as the master production scheduling and MRP processes in multi-level MRP systems. Zhao et al. (1995) and Zhao and Xie (1998) also investigated the impact of lot-sizing rule selection on the selection of MPS freezing parameters under demand uncertainty.

Kadipasaoglu and Sridharan (1995) evaluated the effectiveness of three strategies for reducing nervousness in multi-stage MRP systems under demand uncertainty and found that freezing the MPS was the most effective approach in terms of reducing both instability and cost. In another study, Kadipasaoglu and Sridharan (1997) improved their earlier measure of SI in a multi-stage MRP system. Ho and Ireland (1998) examined the impact of forecasting errors on the scheduling instability in an MRP operating environment. They found that a higher degree of forecasting errors may not cause a higher degree of SI and the selection of an appropriate lot-sizing rule can mitigate SI. Therefore, the selection of lot-sizing rules might be more important than minimizing forecasting errors.

Ho and Carter (1996) evaluated the effectiveness of three rescheduling procedures for dampening the nervousness in a multi-stage MRP system by using a factory-2 simulator under uncertainty. The uncertainty was introduced by generating changes in the MPS and altering the scrap rate of production. They used the uncapacitated lot-for-lot (LFL) and the economic ordering quantity (EOQ) rules to develop the MPS, while capacity constraints in the job shop are equivalent to overall utilization rates of 60 and 80%, respectively. Under their experimental settings, they found that the performance of a dampening procedure depended on the operating environment of the firm. They also found that the reduction of system nervousness, as measured by the frequency of schedule disruptions, does not lead to a better system performance. The appropriate deployment of either a dampening procedure or lot-sizing rules was found to have the potential to contribute to system improvement.

Recently, Yeung, Wong, and Ma (1998) provided an intensive review of the literature that examines the parameters affecting the effectiveness of MRP systems. They pointed out that one of the major limitations of previous research is that capacity constraints are not included in most of the studies. Zhao and Lee (1993, 1996) and Zhao et al. (1995) expressed the same view. Actually, our literature review shows that only Ho and Carter (1996) and Zhao et al. (2001) considered capacity constraints. Ho and Carter (1996) considered limited capacity in the job shop in studying the effectiveness of three procedures for dampening MRP nervousness. However, they did not consider capacity constraints in developing the MPS. Zhao et al. (2001) studied the impact of MPS freezing parameters on the performance of multi-item, single-level production systems with a single resource constraint and deterministic demand. It is not yet known whether the conclusions they arrived at without considering capacity constraints or systems under deterministic demand will be valid under capacitated situations with demand uncertainty. This study attempts to fill this gap in the literature by investigating the performance of MPS freezing parameters in a multi-item system under a single resource constraint and demand uncertainty.

To investigate the impact of MPS freezing on system performance under a single resource constraint, we must first select an appropriate lot-sizing rule under a capacity constraint. Many researchers have studied lot-sizing problems for multi-item, single-level production and inventory systems with a single resource constraint. Maes and Van Wassenhove (1988) provided a general review and experimental comparison of the performance for most of the multi-item, single-level capacitated dynamic lot-sizing rules, which can be found in the literature. Some review papers on multi-stage, lot-sizing problems also include a section on multi-item, single-level capacitated lot-sizing (Eftekharzadeh, 1993; Kuik and Salomon, 1994; Simpson and Erenguc, 1996). Considering the computation requirements under a rolling planning environment, as well as practical implications, this study will use the lot-sizing algorithm proposed by Dixon and Silver (1981), which has been shown to perform well in terms of computation times and cost performance (Maes and Van Wassenhove, 1986; Gunther, 1988).

To investigate the impact of MPS freezing on system performance under demand uncertainty through computer simulation, we must obtain the demand forecasts, since master production scheduling is based on the demand forecasts rather than actual demand under demand uncertainty. Two alternative approaches have been used to produce the forecasts in previous studies. One approach is to generate the forecasting error according to some probability distribution and add it to the actual demand. The other is to use a forecasting model to make forecasts based on previous demand. The first approach was used by Lee and Adam (1986), Sridharan and Berry (1990a), Sridharan and LaForge (1990 and 1994), etc. while the second approach was used by Zhao and Lee (1993), Zhao et al. (1995), etc. This study adopts the first approach to generate the demand forecasts.

3. Research design

The methodology used in this study is computer simulation. This section describes the design and implementation of the simulation model and summarizes the independent and dependent variables of the experimental design.

3.1. Simulation procedures

The simulated manufacturing company is assumed to operate in a make-to-stock environment and production scheduling is based on demand forecast and available capacity under rolling time horizons. The company is assumed to produce five different finished products, all requiring a single aggregate resource. It is also assumed that no dependency or absorption relationships exist among these products. The lead-times for all the items are assumed to be zero. Demand, order releases and order receipts all occur at the end of the periods and all orders must be satisfied whenever possible. If there is not sufficient capacity to produce all the products demanded, the maximum quantity possible is produced, and demand not satisfied will become loss of sales. This reflects a major difference between the manufacturing system with a capacity constraint as assumed in this study and the system without any capacity constraints. The simulation model consists of three phases, which are discussed below.

Phase I: Demand and capacity generation.The first phase of the simulation generates demand for all the products and the available aggregate capacity, which represents a single resource. The overall market and the detailed product mix are two crucial concerns of demand management (Vollmann, Berry, & Whybark, 1992). Therefore, the following demand generation function is used to generate demand for each of the five items during 400 periods:

$$D_{it} = 5000 \times (1 + 0.4 \times R_1) \times p_i \times (1 + 0.4 \times R_2), \tag{1}$$

where D_{it} is the demand for item $i(1 \leq i \leq 5)$ in period $t(1 \leq t \leq 400)$, R_1 and R_2 are standard normal random variants, and p_i is the mean demand proportion for item i (in this study, p_i is set at 20, 10, 25, 15, 30% for $i = 1, 2, 3, 4, 5$, respectively). That's to say, the mean total demand for all five items in each period is 5000 units and the mean demands in each period are 1000, 500, 1250, 750 and 1500 units for items 1–5, respectively. Furthermore, the first random factor $(1 + 0.4 \times R_1)$ represents the magnitude of the noise component for total demand and the second random factor $(1 + 0.4 \times R_2)$ represents the magnitude of the noise component for product mix. In order to make the demands D_{it} non-negative, we set a lower and an upper bound on the standard normal random variant at -2.5 and $+2.5$, respectively.

The available capacity is generated by varying the capacity tightness (CT) parameter. CT is defined as the ratio between the total capacity available and the total capacity needed, which is the inverse of capacity utilization. In this study, we assume that the capacity absorption for each unit of each item is equal to one. That is, one unit of the resource is required to produce exactly one unit of each finished product. Relaxing this assumption will not influence the conclusion because the demand for each product can always be measured by the units of the resource needed to produce the product. Once the demand for all items is generated for the 400 periods, the total demand for these 400 periods is calculated. Then the total capacity needed to produce all of the items can be calculated by multiplying the total demand by the CT factor. We assume that the capacity available in each period is a constant in the entire simulation run and, thus, is equal to the total capacity available divided by the total number of periods (400 in this study).

Phase II: Forecast generation. The forecasting errors are assumed to be normally distributed and are characterized by two parameters: the mean (also called bias) of forecast errors (EB) and the initial standard deviation (ED) that measures forecast variability. Hence, the demand forecast made at period t_0 for a period $t(t \geq t_0)$ is generated according to the following formula:

$$F_{it} = D_{it} \times (1 + \mathrm{EB}) \times (1 + \mathrm{ED} \times (t - t_0 + 1) \times R), \tag{2}$$

where D_{it} is the demand for item i in period t as generated in Eq. (1) and R is a standard normal random number.

Phase III: MPS development. The third phase of the simulation model develops the MPS in a rolling time horizon environment, using the set of parameters generated in phases I and II. The development of the MPS schedules depends on the following three MPS freezing parameters: the planning horizon (PH), the freezing proportion (FP) and the replanning proportion (RP). The PH is defined as the number of periods for which the production schedules are developed in each replanning cycle. The FP refers to the ratio of the frozen interval relative to the PH. The RP is the ratio of the replanning periodicity (the number of periods between successive replannings) relative to the frozen interval.

The production schedule is developed for the entire PH in each replanning cycle based on demand forecasts, but only the schedules within the freezing interval are implemented as originally planned. Beyond the frozen interval, the MPS is subject to revision. In each replanning cycle, the production schedule is rolled a certain number of periods (replanning periodicity) ahead, and the demand forecasts for periods in the previous PH will be revised, while the demand forecasts for more distant future periods (not previously scheduled) are appended to the schedule. After the net requirements are determined for a number of periods into the future (PH), the MPS can be developed for these periods by utilizing the DS rule (Dixon and Silver, 1981).

This process of replanning under a rolling horizon is repeated until an MPS is developed for all simulation periods. After an MPS has been developed and implemented for all items, performance measures are calculated to evaluate the performance of the production systems.

3.2. Independent variables

The experimental factors used in this simulation experiment are listed in Table 1. These factors can be classified into three groups. The first group of independent variables consists of the 'environmental factors' or 'operating conditions' of the systems, which include CT, maximum natural ordering cycle (T) and unit shortage cost (SC). The second group of independent variables consists of the parameters for forecasting error distributions, which include EB and ED, as shown in Eq. (2). The third group of independent variables consists of the parameters for freezing MPS, which include the PH, FP and RP.

In this study, CT is set at 1.25, 1.11 and 1.01, respectively, to represent low, medium and high levels of CT. The three levels of CT correspond to 80, 90 and 99% of resource utilization, respectively.

Besides CT, other operating factors include the maximum natural ordering cycle (T) and the unit SC. Inventory carrying cost and production setup cost/ordering cost are two major cost parameters in MPS settings. Similar to Zhao and Xie (1998), the unit holding cost per period for each item is randomly generated from the set [0.1, 0.5, 1.0, 2.0] and then is fixed for all of the testing problems. The natural ordering cycle for item 1 is assumed to be the maximum cycle among all items. The setup cost for item 1 is varied so that the natural ordering cycle for this item (T) is 4 and 8 periods, respectively. The setup costs for the other items (items 2, 3, 4 and 5) are designed so that their natural ordering cycles are randomly selected from the set [1,2,…,T] and then fixed for all testing problems. In this simulation experiment, shortages can occur as a result of insufficient capacity in certain periods during any replanning cycle. The unit SC for an item is assumed to be SC times the unit value of the item, which is used to reflect loss of profit and the negative effect on future sales. Assuming that a period is a week

Table 1
Experimental factors

Factor no.	Factor name	Label	No. of levels	Values
1	Capacity tightness	CT	3	Low, medium, high
2	Maximum natural ordering cycle	T	2	4 and 8 periods
3	Unit shortage cost	SC	3	Low, medium, high
4	Forecast error bias	EB	4	−0.05, 0.00, 0.05, 0.10
5	Forecast error deviation	ED	3	0.00, 0.05, 0.10
6	Planning horizon	PH	2	4T and 8T
7	Freezing proportion	FP	5	0.00, 0.25, 0.50, 0.75, 1.00
8	Replanning proportion	RP	4	0.25, 0.50, 0.75, 1.00

Table 2
Cost parameters

Item	Unit holding cost ($/unit/period)	Production Setup cost ($/setup)		Unit Shortage cost ($/unit)		
		T = 4	T = 8	SC = Low	SC = Medium	SC = High
Item 1	1.00	8000	32000	20	40	80
Item 2	0.50	500	2000	10	20	40
Item 3	1.00	625	2500	20	40	80
Item 4	2.00	3000	12000	40	80	160
Item 5	1.00	3000	12000	20	40	80

and the unit holding cost per year (52 weeks) of an item is 26% of the unit value, the unit value for an item is 52/26% (= 200) times the unit holding cost per period for the item. In this study, the SC is set at 10, 20 and 40% of the item value for the low, medium and high levels of SCs, respectively. Table 2 shows the cost parameters generated using this procedure.

In this study, we set the EB values at −0.05, 0, 0.05 and 0.10 and the ED values at 0, 0.05 and 0.10, respectively. For the MPS freezing parameters, the PH is set at $(4T, 8T)$, the FP is set at 0.00, 0.25, 0.50, 0.75, 1.00 and the RP is set at 0.25, 0.50, 0.75, 1.00, respectively. An FP of 0.00 means that the frozen interval is equal to one period and this case is used as a benchmark for evaluating the performance of FP.

3.3. Dependent variables

The following three criteria will be used as the dependent variables in the experimental design:

Total cost (TC), which is the sum of the production setup cost, inventory carrying cost and the SC for all items within the length of the simulation run

Schedule instability or nervousness (SI), which is measured by the following equation

$$I = \frac{\sum_{i=1}^{n} \sum_{k>1} \sum_{t=M_k}^{M_k+N-1} |Q_{ti}^{k} - Q_{ti}^{k-1}|}{S}, \tag{3}$$

where

i, item index;
n, total number of items;
t, time period;
k, planning cycle;
Q_{ti}^{k}, scheduled order quantity for item i in period t during planning cycle k;
M_k, beginning period of planning cycle k;
N, length of PH; and
S, total number of orders in all planning cycles.

A similar formula was used by Sridharan et al. (1988) to measure MPS instability in single-level uncapacitated systems.

Service level (SL), which is the ratio of the cumulative production quantity (i.e. the original cumulative demand minus cumulative shortage due to capacity limitation) to the original cumulative total demand for all items.

The values of the dependent variables are computed for each combination of independent variables. For each combination of independent variables, five runs are made to reduce random effects. The data will be analyzed using the Analysis of Variance (ANOVA) procedure to test the hypotheses presented in Section 4.

4. Research hypotheses

Four general hypotheses are tested in this study.

Hypothesis 1. The parameters for freezing the MPS will significantly influence the total cost, SI and SL of multi-item, single-level systems with a single resource constraint under demand uncertainty.

Hypothesis 2. The forecasting errors (EB, ED) will significantly influence the total cost, SI and SL of multi-item, single-level systems with a single resource constraint under demand uncertainty.

Hypothesis 3. The forecasting errors (EB, ED) will significantly influence the performance of the parameters for freezing the MPS. The selection of MPS freezing parameters will be significantly influenced by forecasting errors.

Hypothesis 4. Environmental factors (CT, DV, MV, T, SC) will significantly influence the performance of the parameters for freezing the MPS. The selection of MPS freezing parameters will be significantly influenced by environmental factors.

5. Results and analyses

In order to test the above hypotheses, the simulation output was analyzed using the ANOVA procedure. To meet the assumptions of ANOVA, the logarithm transformation of TC, SI and square transformations of SL are made based on residual analysis and suggestions in the SAS package. The results shows that most of the main two-way and three-way interaction effects are significant in influencing TC, SI and SL at the 5% significance level. The results are presented around the above hypotheses.

5.1. Overall performance of MPS freezing parameters

To compare the performance of the freezing parameters, the relative total costs (RTC), the relative schedule instabilities (RSI) and the SLs using different MPS freezing parameters are shown in Table 3

Table 3
Overall performance of MPS freezing parameters

Dependent variables		Total cost		Schedule instability		Service level	
Independent variables	Values	RTC[a]	RANK[b]	RSI[c]	RANK[b]	SL[d]	RANK[b]
Planning horizon (PH)	4	100	1	100	1	97.57	2
	8	103	2	220	2	97.85	1
Freezing proportion (FP)	0.00	100	1	4617	5	98.83	1
	0.25	107	2	823	4	98.08	2
	0.50	114	3	294	3	97.79	3
	0.75	121	4	100	2	97.48	4
	1.00	138	5	0	1	96.37	5
Replanning periodicity (RP)	0.25	111	4	127	4	97.20	4
	0.50	106	3	109	3	97.67	3
	0.75	103	2	103	2	97.90	2
	1.00	100	1	100	1	98.07	1

[a] RTC represents relative total cost. For each independent variable, the lowest total cost among all its values is set at 100. The RTCs of the other values of this independent variable are obtained by dividing the lowest total cost into the total costs of these values.

[b] RANK represents relative rank of the MPS freezing parameters and is obtained using Duncan's multiple-range test with a significance level of 5%.

[c] RSI represents relative schedule instability. For each independent variable, the lowest non-zero SI among all its values is set at 100. The RSIs of the other values of this independent variable are obtained by dividing the lowest non-zero SI into the schedule instabilities of these values.

[d] SL represents service level. It is the % of the demand satisfied.

The RTC and the RSI are calculated by dividing the lowest TC and the lowest SI (set to 100 as benchmark) into the TC and SI for a specific parameter value. The performance of each MPS freezing parameter is ranked using Duncan's multiple-range test and are also shown in Table 3. We found that a longer PH resulted in a higher TC, a higher SI and also a higher SL. A larger FP produces a higher TC, lower SI and a lower SL. A larger RP produces a lower TC, a lower SI and a higher SL. These findings indicate that in order to improve the performance of the capacitated production system, the RP should be set at 1.0. However, a trade-off must be made between TC, SI and SL in the selection of PH and FP. The comparisons of the results in Table 3 with those reported by previous studies under no capacity constraints or deterministic demand are summarized in Table 4.

In summary, the results in Tables 3 and 4 indicate that the parameters for freezing the MPS significantly influence the TC, SI and SL of multi-item, single-level systems under a single resource constraint and demand uncertainty. Overall, the results support Hypothesis 1. The comparison of the research findings of this study with those of other studies in Table 4 shows that the conclusions from studies under demand uncertainty and no capacity constraints can be generalized to the case of having a single resource constraint under demand uncertainty. When the findings from the case of single resource constraint under demand uncertainty are compared with those under deterministic demand, the only conclusion that is different is the performance of the PH. While a longer PH results in a lower total cost under deterministic demand, it results in a higher total cost under demand uncertainty.

Table 4
Comparison of the overall performance of MPS freezing parameters

	Uncapacitated system		Capacitated system	
	Deterministic demand	Uncertain demand	Deterministic demand (ZXJ,2001)	Uncertain demand (This study)
TC (Total cost)				
Planning horizon ⇑	⇓ (SBU,1987 and SB, 1990b)	⇑ (SB, 1990a)	⇓	⇑
Freezing proportion ⇑	⇑ (SBU, 1987 and SB, 1990b)	⇑ (SB, 1990a and SL, 1994)	⇑	⇑
Replanning periodicity ⇑	⇓ (SB, 1990b)	⇓ (SB, 1990a)	⇓	⇓
SI (Schedule instability)				
Planning horizon ⇑	⇑ at first and then ⇓ (SBU, 1988) ⇑ (WW) and ⇓ (SM) (SB, 1990b)	⇑ (SB, 1990a)	⇑	⇑
Freezing proportion ⇑	⇓ (SBU, 1988 and SB, 1990b)	⇓ (SB, 1990a and SL, 1990)	⇓	⇓
Replanning periodicity ⇑	⇓ (SB, 1990b)	⇓ (SB, 1990a)	⇓	⇓
SL (Service Level)				
Planning horizon ⇑	N/A	Not clearly addressed	⇑	⇑
Freezing proportion ⇑	N/A	⇓ (SL,1990) X (SL, 1994)	⇓	⇓
Replanning periodicity ⇑	N/A	Not clearly addressed	⇑	⇑

'⇑' means 'increase', '⇓' means 'decrease', 'X' means 'remain almost the same', and 'N/A' means 'not applicable'. 'WW' means using the Wagner-Whitin lot-sizing rule and 'SM' means using the Silver-Meal lot-sizing rule. The references: SBU, 1987: Sridharan, Berry and Udayabhanu (1987); SBU, 1988: Sridharan, Berry and Udayabhanu (1988); SB, 1990a: Sridharan and Berry (1990a); SB, 1990b: Sridharan and Berry (1990b); SL, 1990: Sridharan and LaForge (1990); SL, 1994: Sridharan and LaForge (1994); ZXJ, 2001: Zhao, Xie, and Jiang (2001).

5.2. Overall performance of forecasting errors

The overall performance of EB and ED according to TC, SI and SL is shown in Figs 1–3 , respectively. From these figures, we can see that the perfect forecast (i.e. EB = ED = 0) performs best according to TC and SI. However, when EB increases from 0 to a positive value, TC, SI and SL all increases. That's to say, a positive bias usually improves the SL of the system. The reason is that when there is a positive bias in the forecasted demand, the system will try to make better use of its capacity and produce more products than needed; thus, the SL is increased. Although this will reduce

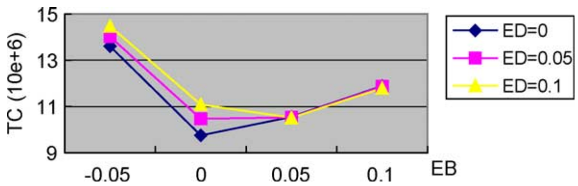

Fig. 1. Performance of EB and ED according to TC.

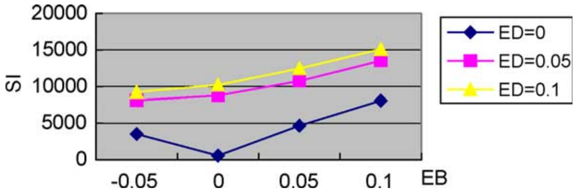

Fig. 2. Performance of EB and ED according to SI.

the SC, it also increases the setup and inventory costs. Thus, the total cost is increased. Besides, when there is a positive bias, the planned orders in previous planning cycle will usually exceed the actual demands and thus, these orders need to be modified in the planning cycles that follow. Therefore, the SI is also increased.

When there is a negative bias, TC increases and SL decreases. This is because the system will produce fewer products than needed. Thus, the SL is reduced and the SC is significantly increased. For SI, a negative bias results in a slightly lower SI than that of no forecast bias under ED $= 0.05$ and 0.1, but a slightly higher SI under ED $= 0$.

Examinations of these figures also show that when ED increases, both TC and SI increase and SL decreases, no matter what value EB takes. This observation reveals the negative effect of the standard deviation of the forecast error.

These observations reveal that an accurate demand forecast can significantly improve the performance of the production systems according to TC and SI. However, a positive forecast bias could increase the SLs of the systems. These observations support Hypothesis 2.

5.3. Interaction between forecasting errors and MPS freezing parameters

To examine the impact of forecasting errors on the performance of the MPS freezing parameters, Duncan's multiple-range test was performed to rank the performance of PH, FP and RP under different values of EB and ED. The examinations reveal that ED does not influence the relative ranking of the MPS freezing parameters according to all three measures, while EB does not influence the relative ranking of FP and RP according to all three measures and the relative ranking of PH according to SI and SL. However, according to TC, the relative ranking of PH is influenced by the EB factor, which is shown in Fig. 4.

From Fig. 4, we can see that when the forecasting bias is zero or negative, a shorter PH (PH $= 4T$) results in a higher total cost than a longer PH (PH $= 8T$), which agrees with the previous finding under deterministic demand. However, the reverse is true under positive forecasting bias. This result indicates

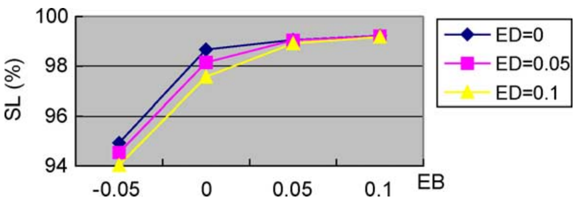

Fig. 3. Performance of EB and ED according to SL.

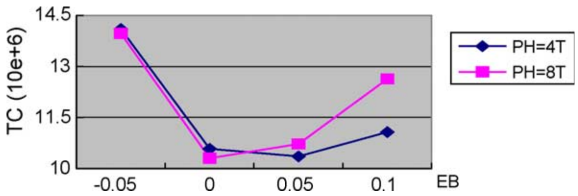

Fig. 4. Impact of EB on PH according to TC.

that in order to improve the performance of the capacitated production system, the effects of forecasting errors (especially the forecasting error bias) should be taken into consideration when determining the proper PH.

Overall, these observations reveal that Hypothesis 3 is only partially supported.

5.4. Performance of forecasting errors under different operating conditions

Duncan's multiple-range tests reveal that operating conditions do not influence the relative ranking of ED according to all three performance measures and the relative ranking of EB according to SI and SL. According to TC, only CT and SC influence the relative ranking of EB and the results are plotted in Figs. 5 and 6, respectively.

From Figs. 5 and 6, we can see that when CT or SC is 'high,' the total cost decreases slowly as EB increases from 0 to 0.05, then increases as EB increases from 0.05 to 0.10. Under other conditions, total cost always increases as EB increases. This finding indicates that a slight positive bias can reduce the total cost of the production system when the capacity is very tight or the shortage punishment is very high.

These observations partially support Hypothesis 4.

6. Discussions and conclusions

This study extends earlier studies of freezing the MPS from a single-level system without any capacity constraints or without demand uncertainty to a system with a single resource capacity constraint under

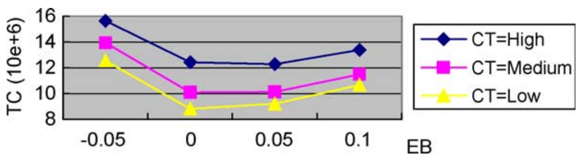

Fig. 5. TC performance of EB under different CT.

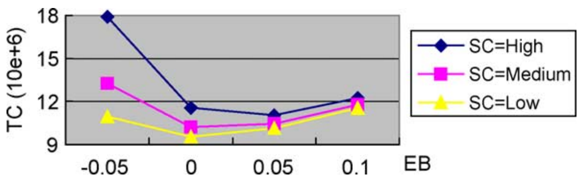

Fig. 6. TC performance of EB under different SC.

demand uncertainty. This paper investigates the impact of the parameters for freezing the MPS on the total cost, SI and SL of multi-item, single-level systems with a single resource constraint. It also examines the impact of forecasting errors on the selection of MPS freezing parameters under rolling time horizons and demand uncertainty. Through comprehensive computer simulations and statistical analyses, we find the following:

1. The length of the PH, the FP and the replanning periodicity all significantly influence the total cost, SI and SL in multi-item, single-level systems under demand uncertainty. To select the proper FP and PH, trade-offs between total cost, SL and SI have to be made, while the longest replanning periodicity always results in the best performance.
2. The two-way interaction between MPS freezing parameters and the forecasting errors significantly influences the performance of the system. Although the forecasting errors do not influence most of the relative performance rankings of the FP and RP parameters, the relative performance ranking of the PH parameter in terms of total cost can be influenced by the bias of the forecasting error.
3. Although a more exact forecast results in better performance for the system under most of the conditions, a moderate positive bias can improve the performance for the system when the capacity is very tight or the shortage punishment is very high.

The above findings can help production planners select better MPS freezing parameters under different operating conditions. The results of this study also enhance our knowledge and understanding of the performance of MPS freezing parameters and forecasting errors under capacity constraints and demand uncertainty.

Although the study makes a significant contribution to the academic literature and to practical applications, it also has several limitations. Future research is needed to better understand the impact of MPS freezing parameters on system performance under capacity constraints. The following future research avenues may be pursued:

1. The experimental settings in this study include master production scheduling in multi-item, single-level systems under a single resource constraint. While a single-level study will provide insight into the problem, more insight can be gained by conducting the study on a multi-level system. Over the years, many procedures have been suggested to solve multi-level capacitated lot-sizing problems under static horizons, but these procedures have not been tested under a rolling time horizon in combination with MPS freezing. In multi-level MRP systems, the interaction effects between the freezing parameters, forecasting errors, lot-sizing rules and other factors will be very complex. Investigation of these interaction effects on MRP system performance should provide further insight into MPS freezing under capacity constraints.
2. This study only included one simple capacitated lot-sizing rule. Many other capacitated lot-sizing rules have been reported in the literature. It would be useful to check the validity of the conclusion from this study by using more lot-sizing rules.
3. In this study, we assumed that there are no seasonality and trends in the demand patterns. It will be interesting to examine the impact of demand patterns on the selection of MPS freezing parameters and on the performance of the forecasting errors under different operating conditions.

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References

Blackburn, J. D., Kropp, D. H., & Millen, R. A. (1986). A comparison of strategies to dampen nervousness in MRP systems. *Management Science*, *32*, 413–429.

Blackburn, J. D., Kropp, D. H., & Millen, R. A. (1987). Alternative approaches to schedule instability: a comparative analysis. *International Journal of Production Research*, *25*, 1739–1749.

Dixon, P. S., & Silver, R. A. (1981). A heuristic solution procedure for the multi-item single level, limited capacity, lot sizing problem. *Journal of Operations Management*, *2*, 23–29.

Eftekharzadeh, R. (1993). A comprehensive review of production lot-sizing. *International Journal of Physical Distribution and Logistic Management*, *23*, 30–44.

Gunther, H. O. (1988). Numerical evaluation of heuristics for the multi-item single-level capacitated lot-size problem. *Engineering Costs and Production Economics*, *14*, 233–243.

Ho, C. J., & Carter, P. L. (1996). An investigation of alternative dampening procedures to cope with MRP system nervousness. *International Journal of Production Research*, *34*, 137–156.

Ho, C. J., & Ireland, T. C. (1998). Correlating MRP system nervousness with forecast errors. *International Journal of Production Research*, *36*, 2289–2299.

Kadipasaoglu, S. N., & Sridharan, V. (1995). Alternative approaches for reducing schedule instability in multistage manufacturing under demand uncertainty. *Journal of Operations Management*, *13*, 193–211.

Kadipasaoglu, S. N., & Sridharan, V. (1997). Measurement of instability in multi-stage MRP systems. *International Journal of Production Research*, *35*, 713–737.

Kuik, R., & Salomon, M. (1994). Batching decision: structure and models. *European Journal of Operational Research*, *75*, 243–263.

Lee, T. S., & Adam, E. E., Jr (1986). Forecasting error evaluation in material requirements planning (MRP) production-inventory systems. *Management Science*, *32*, 1186–1205.

Lin, N., & Krajewski, L. J. (1992). A model for master production scheduling in uncertain environments. *Decision Sciences*, *23*, 839–861.

Maes, J., & Van Wassenhove, L. N. (1988). Multi-item single level capacitated dynamic lot sizing heuristics: a general review. *Journal of the Operational Research Society*, *39*, 991–1004.

Simpson, N. C., & Erenguc, S. S. (1996). Multi-stage production planning research: history and opportunities. *International Journal of Operations and Production Management*, *16*, 25–40.

Sridharan, S. V., & Berry, W. L. (1990a). Freezing the master production schedule under demand uncertainty. *Decision Sciences*, *21*, 97–120.

Sridharan, S. V., & Berry, W. L. (1990b). Master production scheduling, make-to-stock products: a framework for analysis. *International Journal of Production Research*, *28*, 541–558.

Sridharan, S. V., Berry, W. L., & Udayabhanu, V. (1987). Freezing the master production schedule under rolling planning horizons. *Management Science*, *33*, 1137–1149.

Sridharan, S. V., Berry, W. L., & Udayabhanu, V. (1988). Measuring master production schedule stability under rolling planning horizons. *Decision Sciences*, *19*, 147–166.

Sridharan, S. V., & LaForge, R. L. (1990). An analysis of alternative policies to achieve schedule instability. *Journal of Manufacturing and Operations Management*, *3*, 53–73.

Sridharan, S. V., & LaForge, R. L. (1994). Freezing the master production schedule: implications for the fill rate. *Decision Sciences*, *25*, 461–469.

Vollmann, T. E., Berry, W. L., & Whybark, D. L. (1992). Manufacturing planning and control systems (3rd ed.). Homewood, IL: Irwin.

Yeung, J. H. Y., Wong, W. C. K., & Ma, L. (1998). Parameters affecting the effectiveness of MRP systems: a review. *International Journal of Production Research*, *36*, 313–331.

Zhao, X., & Lam, K. (1997). Lot-sizing rules and freezing the master production schedule in material requirements planning systems. *International Journal of Production Economics*, *53*, 281–305.

Zhao, X., & Lee, T. S. (1993). Freezing the master production schedule in multilevel material requirements planning systems under demand uncertainty. *Journal of Operations Management*, *11*, 185–205.

Zhao, X., & Lee, T. S. (1996). Freezing the master production schedule for material requirements planning systems under deterministic demand. *Production Planning and Control*, *7*, 144–161.

Zhao, X., Goodale, J., & Lee, T. S. (1995). Lot-sizing rules and freezing the master production schedule in MRP systems under demand uncertainty. *International Journal of Production Research*, *33*, 2241–2276.

Zhao, X., & Xie, J. (1998). Multilevel lot-sizing heuristics and freezing the master production schedule in material requirements planning systems. *Production Planning and Control*, *9*, 371–384.

Zhao, X., Xie, J., & Jiang, Q. (2001). Lot-sizing rule and freezing the master production schedule under capacity constraint and deterministic demand. *Production and Operations Management*, *10*, 45–67.