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# Freezing the master production schedule under single resource constraint and demand uncertainty

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### Abstract

This paper investigates the impact of freezing the master production schedule (MPS) in multi-item single-level systems with a single resource constraint under demand uncertainty. It also examines the impact of environmental factors on the selection of MPS freezing parameters. A computer model is built to simulate master production scheduling activities in a multi-item system under a rolling time horizon. The result of the study shows that the parameters for freezing the MPS have a significant impact on total cost, schedule instability and the service level of the system. Furthermore, the selection of freezing parameters is also significantly influenced by some environmental factors such as capacity tightness and cost structure. While some findings concerning the performance of MPS freezing parameters without capacity constraints can be generalised to the case of limited capacity, other conclusions under capacity constraints are different from those without capacity constraints.
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## 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 and service level of a production inventory system. The MPS drives the material requirements planning (MRP) system and provides the important link between the 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 hand. 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 customer service level. This phenomenon is called "schedule instability" or "MRP nervousness". Maintaining a stable MPS in view of changing customer requirements, adjustments in sales forecasts, and unforeseen suppliers or production problems is a difficult proposition for many firms (Sridharan et al., 1988).

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Several methods have been suggested to reduce schedule instability in MRP systems (Blackburn et al., 1986, 1987). One frequently used method involves the freezing of the MPS. Several studies have proposed alternative ways of freezing the MPS (Sridharan et al., 1987, 1988) and have compared the effectiveness of freezing the MPS against other methods (Sridharan and LaForge, 1990; Kadipasaoglu and Sridharan, 1995). Zhao and Lee (1993, 1996) examined the impact of different parameters for freezing the MPS upon total cost, schedule instability and service level in multi-stage systems. Zhao and his co-workers (Zhao and Lam, 1997; Zhao et al., 1995; Zhao and 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. Since most production systems have capacity constraints and the master production scheduler has to take into consideration these constraints in developing the MPS, it is important to include capacity constraint in MPS studies. Therefore, it is of significant academic and practical value to know whether the conclusions and guidelines drawn under the assumption of unlimited capacity can be applied in the more realistic cases of having limited capacity. Investigations of the impact of capacity constraint on the selection of MPS freezing parameters will provide guidelines for practitioners to choose the proper set of MPS freezing parameters to enhance system performance.

Recently, 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. They found that some of the conclusions without considering capacity constraints could not be generalised 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 decision. They often use the same capacity to manufacture several products. Developing and maintaining MPS under capacity constraints and demand uncertainty is far more challenging than doing that 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. There are three major reasons for us to investigate this issue in the single-level system under a single resource constraint. Firstly, this makes the lot-sizing decisions relatively easy to make. If we consider multi-level system with multiple resources as constraints, it will be much more difficult to make the lot-sizing decisions. Secondly, although multiple resources might be needed to produce a product, one critical resource often limits the production output of a company. This is commonly called ''bottleneck'' of the company. When the master production scheduler develops the master production schedule, he/she will mainly consider this constraint in developing the master production schedule. Thirdly, although most products have multiple levels in the bill of material and detailed capacity requirements can only be derived from the material requirements plan, the bill of material and the routing data, most master production schedulers do not go to this level of details in developing MPS. In developing MPS, they only do a rough-cut capacity plan to see whether the MPS is feasible. When we consider the aggregate capacity requirement of the critical resource in developing the master production schedule, we can treat the system as a single-level system. In summary, we decided to investigate the issue in single-level MPS system under a single resource constraint in order for us to realistically focus on the most important aspect of the problem.

Specifically, we will do the following:

(1) investigate the impact of freezing the MPS on the performance of multi-item single-level

systems with a single resource constraint under demand uncertainty; and

(2) study the impact of environmental factors on the selection of MPS freezing parameters under demand uncertainty.

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

## 2. Related research

Because of the importance of maintaining a stable MPS and the difficulty of balancing the cost, schedule instability and customer service level in making MPS freezing decisions, a number of researchers have investigated alternative methods to reduce schedule instability. Blackburn et al. (1986, 1987) investigated five different strategies for reducing MRP nervousness and found freezing the MPS to be among the most effective strategies. Sridharan et al. (1987, 1988) developed a method to measure schedule instability and studied the impact of MPS freezing upon inventory costs and schedule instability 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 schedule instability of the system. Sridharan and Berry (1990a), Sridharan and LaForge (1990, 1994), Lin and Krajewski (1992) 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 found that some findings in single-level systems cannot be generalised 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 schedule instability in 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 schedule instability and the selection of an appropriate lot-sizing rule can mitigate schedule instability. Therefore, the selection of lot-sizing rules might be more important than the minimising of forecasting errors.

Ho and Carter (1996) evaluated the effectiveness of three rescheduling procedures for dampening the nervousness in a multi-stage MRP system 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 an overall utilisation 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. Appropriate deployment of a dampening procedure and lot-sizing rules was found to be able to contribute to system improvement.

Recently, Yeung et al. (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 unknown whether the conclusions without considering capacity constraints or 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. This problem consists of scheduling $n$ items over a horizon of $N$ periods. In this problem, demands are given and should be satisfied without backlogging. The objective is to minimise the sum of set-up and inventory-holding costs over the entire planning horizon subject to an aggregate capacity constraint in each period. 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). Zhao et al. (2001)

evaluated four capacitated lot-sizing rules under rolling horizon and found that the selection of lot-sizing rules did not influence the selection of the MPS freezing parameters. Considering the computation requirements under a rolling planning environment and practical implications, this study only uses one lot-sizing procedure from the four attractive heuristic procedures tested in Zhao et al. (2001): the algorithm proposed by Dixon and Silver (1981) (the DS rule). The DS rule has been shown to perform well in terms of computation times and cost performance (Maes and Van Wassenhove, 1988; 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 mater production scheduling is based on the demand forecasts rather than actual demands 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 forecast based on previous demands. The first approach was used by Lee and Adam (1986), Sridharan and Berry (1990a) and Sridharan and LaForge (1990, 1994), etc., while the second approach was used by Zhao and Lee (1993) and Zhao et al. (1995), etc. This study will adapt the second approach and uses the moving average model to forecast future demands based on previous demands.

## 3. Research design

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

### 3.1. Simulation procedures

The simulated manufacturing company mimics a real company that we visited in Hong Kong. The company operates 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 products all requiring a single critical resource: the machine time. The lead times for all the items are assumed to be zero. Demands, 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, we produce the maximum quantity possible, and demand not satisfied will become loss of sales. This reflects a major difference between the manufacturing system with a capacity constraint as in this study and the system without any capacity constraints. We will further discuss the features of capacitated systems in more detail later in this section.

The simulation model was modified from the one used by Zhao et al. (1995, 2001). The simulation model consists of three phases, which are discussed below.

*Phase I: Generating demand and setting capacity.* The first phase of the simulation generates demand for all the products and then sets the available capacity representing a single resource. The overall market demand and the detailed product mix are two crucial concerns of demand management (Vollmann et al., 1992, p. 322). Therefore, in this study we vary two parameters in the demand distribution: demand variation (DV), which represents the variability of the total demand and product-mix variation (MV), which represents the variability in the proportion of the demand for each of the five products in the total demand. The change in MV reflects the change in demand for each of the five different products as a proportion in the total demand. The following demand generation function is used to generate demands for each of the five items during 400 periods:

$$A_t = A * (1 + \mathrm{DV} * R), \qquad (1)$$

$$A_{it} = A_t * p_i * (1 + \mathrm{MV} * R), \qquad (2)$$

where $I$ is the item index; $t$ the time period index; $A$ the mean total demand per period for all items; $A_t$ the total demand for all items in period $t$; $A_{it}$ the demand for item $i$ in period $t$ (the sum of $A_{it}$ for all $i$ equal to $A_t$); $p_i$ the mean demand proportion for item $i$ (the sum of $p_i$ for all $i$ equal to 1); DV the magnitude of the noise component for total demand, which represents the variability of the total demand; MV the magnitude of the noise component for product mix, which represents the variability in the proportion of the individual items in the total demand; $R$ a standard normal random variant.

The maximum values for MV and DV used in this study are set at 40%. This reflects the range of the value that has been observed by this company in Hong Kong. In order to make the demands $A_t$ and $A_{it}$ non-negative, we set a lower and an upper bound on the standard normal random variant at $-2.5$ and $+2.5$, respectively. The average total demand ($A$), the magnitudes of the random variation component for total demand (DV) and the magnitude of the noise component for product mix (MV) can be varied to generate different demand patterns. In this study, the average total demand $A$ is assumed to be a constant of 5000. The magnitude of the noise component for total demand (DV) is varied at three levels (low, medium, and high) to generate total demands of three different levels of random normal variations. The magnitudes of the noise component for product mix (MV) are also varied at three levels (low, medium and high). There are a total of nine different demand patterns representing different combinations of total demand variations and product-mix variations. Values of these parameters for these demand patterns will be discussed in detail later.

In this study, we assume that one unit of the critical 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.

The available capacity is generated by varying a capacity tightness (CT) parameter. It is defined as the ratio between the total capacity available and the total demand needed, which is the inverse of capacity utilization. In this study, the first 100 periods are used to estimate the forecasting parameter(s) and only the last 300 periods

(from period 101 to period 400) are included in the performance measures. Once the demands for all items are generated for the 400 periods, the total demand for the last 300 periods is calculated. The total capacity available is equal to the total demand multiplied by the CT factor. The capacity per period is equal to the total capacity available divided by the total number of periods and is held constant in the entire simulation run length. This situation is also very similar to the real situation of the company that we visited in Hong Kong. Because it is very expensive to change the machine capacity, the company normally maintains the same constant capacity during the year. Although the company can change the capacity by replacing the old machine with a new one, it is quite expensive to do so. Therefore, capacity is not changed in the short term. This type of situation is quite common when the critical resource is the machine time on an expensive piece of equipment.

*Phase II: Forecasting parameter estimation.* We use moving average (MA), a simple and popular forecasting model, to make forecast for demand in this study. Once the demands for all items are generated for 400 periods, MA is used to make forecasts for the first 100 periods using different forecasting parameters (i.e., the number of periods used to average the demand). The mean absolute deviation (MAD) is calculated to evaluate the performance of different forecasting parameters and the best parameter is selected based on its ability to minimize the one-period-ahead forecasting error measure.

*Phase III: MPS development.* The third phase of the simulation model develops the master production schedule (MPS) in a rolling time horizon environment using the set of parameters generated in phases I and II. The procedure for developing the MPS under capacity constraints and deterministic demand is well described by Zhao et al. (2001). In the following paragraphs, we describe how we dealt with the infeasibility problem arising from the capacity constraint.

The production schedule is developed for the entire planning horizon 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 into a certain number of periods (replanning periodicity) ahead. Since more demand information will become available, the demand forecasts for periods in the previous planning horizon will be revised and demand forecasts for more distant future periods (not previously scheduled) are appended to the schedule. Net requirements for an item for the non-frozen periods within the new planning horizon are calculated using the following equation:

$$\text{Nrequire}(t) = \text{Grequire}(t) - \text{Endinv}(t-1), \qquad (3)$$

where $\text{Nrequire}(t)$ is the net requirement for period $t$, $\text{Grequire}(t)$ is the demand forecasts for period $t$, $\text{Endinv}(t-1)$ is the ending inventory for period $t-1$.

When $\text{Nrequire}(t)$ is less than zero, $\text{Endinv}(t-1)$ is set to minus $\text{Nrequire}(t)$ and $\text{Nrequire}(t)$ is set to zero.

After the net requirements are determined for a number of periods in the future (planning horizon), the MPS can be developed for these periods utilizing the multi-item single-level capacitated lot-sizing rule proposed by Dixon and Silver (1981), which we will refer to as DS rule for simplicity. Under the capacity constraint, however, a feasible MPS for these replanning periods may not exist without backlogging. Obviously, the necessary and sufficient condition for feasibility is that in each period the cumulative capacity needed to produce all net requirements before this period does not exceed the cumulative capacity available before this period. In order to ensure that a feasible MPS can be obtained, the cumulative capacity available is checked against the cumulative net requirement period by period in a forward manner before the lot-sizing heuristics are used to determine the MPS. If capacity is insufficient, the net requirements for one or more items in this period will be reduced by a value to ensure the feasibility. This value is equal to the difference between the cumulative net requirement and the cumulative capacity available up to this period. Requirement for the item with the lowest unit shortage cost will be reduced first, followed by the item with the second lowest unit shortage cost if capacity is still
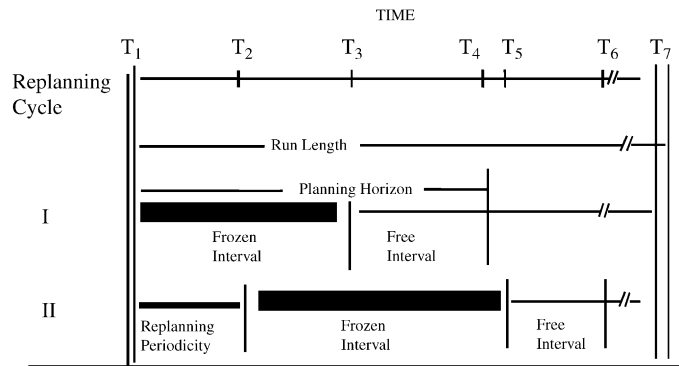
Fig. 1. Demonstration of MPS freezing parameters.

insufficient. This procedure is repeated until capacity is sufficient to ensure a feasible MPS.

After the feasibility check is completed and net requirements for some items revised, the MPS is developed for these periods using the DS rule. To avoid excessive changes, management often chooses to implement a portion of an MPS according to the original plan. The portion of the MPS that is not changed is referred to as "frozen". The number of periods for which MPS schedules are frozen depends on the planning horizon (PH) and the freezing proportion (FP). Fig. 1 illustrates the major parameters for freezing the MPS under a rolling time horizon.

The PH is defined as the number of periods for which the production schedules are developed in each replanning cycle. The frozen interval is the number of scheduled periods within the PH for which the schedules are implemented according to the original plan. The free interval is the number of scheduled periods beyond the frozen interval. This portion is subject to change based on new demand information when the time horizon is rolled forward. The FP refers to the ratio of the frozen interval relative to the PH. The higher the FP, the more stable the production schedule, and the lower the schedule instability of the MPS systems. However, a higher FP may also increase the loss of sales and the total cost.

The replanning periodicity (RP) is the number of periods between successive replannings. When the RP is equal to four periods, demand forecasts for future periods are revised in every four periods and the MPS is revised accordingly. The greater the RP, the less frequently replanning will occur and computational requirements will be reduced. However, a higher RP may also increase both the probability of capacity-related infeasibility (more loss of sales) and total cost.

In addition to the parameters shown in Fig. 1, Sridharan et al. (1987, 1988) suggested two methods of freezing MPS: a period-based method and an order-based method. Using the period-based method, orders within a certain number of periods in the PH are implemented according to the original plan. Using the order-based method, a certain number of orders placed in the PH are implemented as originally planned. Because multiple end-items are involved in this study and each end-item has its own ordering cycle, it is difficult to implement the order-based freezing method. Therefore, we only used the period-based ZM in this study.

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 MRP systems. The simulation procedure is summarised in Fig. 2.

### 3.2. Independent variables

There are two major groups of independent variables in this simulation experiment (Table 1). The first group of independent variables is the "environmental factors" or "operating conditions" of the systems, which includes DV, MV,

| Step A: | Select a demand variation (DV), a product-mix variation (MV) and a capacity tightness (CT); |
| --- | --- |
| | Generate the actual demands and calculate the capacity, then go to step B; |
| Step B: | Select a maximum natural ordering cycle (T), a unit shortage cost (SC), a planning horizon (PH), a freezing proportion (FP) and a replanning periodicity (RP), then go to step C. |
| Step C: | Forecast demands for each item into the periods within current replanning cycle; Calculate the starting period (LS) and the finishing period (LF) for the free interval of current replanning cycle; Calculate forecasted net requirements into the periods within LS and LF; Check the feasibility condition for capacitated lot-sizing and reduce the forecasted demands if necessary; Develop MPS using the capacitated lot-sizing rule for periods between LS and LF; Implement MPS within the frozen interval, calculate the ending inventories, and update performance measures, then go to step D. |
| Step D: | If the end of the simulation has not been reached, roll the schedule RP periods ahead and go to Step C. Otherwise, record the performance measures and go to Step E. |
| Step E: | If all the combinations of different T, SC, PH, FP and RP have been exhausted, then go to step F; Otherwise, go to step B and select at least one different value of T, SC, PH, FP, or RP. |
| Step F: | If all the combinations of different DV, MV and CT have been exhausted, then stop; Otherwise, go to step A and select at least one different value of DV, MV and CT. |

Fig. 2. Simulation procedure.

Table 1
Independent variables of the experimental design

| Variable number | Variable name | Label | Number of levels | Values |
| --- | --- | --- | --- | --- |
| *Operating conditions (environmental factors)* | | | | |
| 1 | Demand variations | DV | 3 | Low, medium, high |
| 2 | Product-mix variations | MV | 3 | Low, medium, high |
| 3 | Capacity tightness | CT | 3 | Low, medium, high |
| 4 | Maximum natural ordering cycle | T | 2 | 4 and 8 periods, respectively |
| 5 | Unit shortage cost | SC | 3 | Low, medium, high |
| | | | | |
| *Parameters for freezing the master production schedule* | | | | |
| 6 | Planning horizon | PH | 2 | 4 and 8 ($*T$) |
| 7 | Freezing proportion | FP | 5 | 0.00, 0.25, 0.50, 0.75, 1.00 |
| 8 | Replanning periodicity | RP | 4 | 0.25, 0.50, 0.75, 1.00 ($*PH*FP$) |

CT, maximum natural ordering cycle ($T$) and unit shortage cost (SC). The second group of independent variables is the parameters for freezing MPS, which includes the PH, the FP and the RP.

### 3.2.1. Environmental factors

*Demand variation* (DV). Three levels of DV factor (shown in Table 2) are used in this study.

DV is set at 10%, 20% and 40% of the average total demand for the three levels, respectively, which represent the low, medium and high levels of variations in the normal random noise component of the total demand for the five products.

*Product-mix variation* (MV). Three levels of MV factor (also shown in Table 2) are used in this study. MV is set at 10%, 20%, and 40% of the

Table 2
Demand parameters

| Average total demand (A) | 5000 | | | | |
|---|---|---|---|---|---|
| Item (I) | 1 | 2 | 3 | 4 | 5 |
| Average demand proportion ($p_i$) (%) | 20 | 10 | 25 | 15 | 30 |
| Average demand | 1000 | 500 | 1250 | 750 | 1500 |
| | | | | | |
| *DV (demand variations) parameters* | | | | | |
| Level | Low | Medium | High | | |
| Value (%) | 10 | 20 | 40 | | |
| | | | | | |
| *MV (Product-mix variations) parameters* | | | | | |
| Level | Low | Medium | High | | |
| Value (%) | 10 | 20 | 40 | | |

Table 3
Cost parameters

| Item | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 |
|---|---|---|---|---|---|
| *Unit holding cost ($/unit/period) (generated randomly from [0.50,1.00,1.50,2.00] and then fixed)* | | | | | |
| All sets | 1.00 | 0.50 | 1.00 | 2.00 | 1.00 |
| | | | | | |
| *Production set-up cost ($/set-up)*[a] | | | | | |
| T = 4 | 8000 (4) | 500 (2) | 625 (1) | 3000 (2) | 3000 (2) |
| T = 8 | 32000 (8) | 2000 (4) | 2500 (2) | 12000 (4) | 12000 (4) |
| | | | | | |
| *Unit shortage cost ($/unit)* | | | | | |
| SC = low | 146 | 73 | 146 | 292 | 146 |
| SC = medium | 292 | 146 | 292 | 584 | 292 |
| SC = high | 584 | 292 | 584 | 1168 | 584 |

[a] The values in the brackets indicate the corresponding natural ordering cycles calculated using the average demand of that item.

average proportion of individual item demand for the three levels, respectively, which represent the low, medium and high levels of variations in the normal random noise component of the product-mix proportion for the five products.

*Capacity tightness* (CT). CT represents the ratio of the total capacity available to the total capacity needed. 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. The total capacity available is equal to the total demand multiplied by CT. The average capacity for each period is equal to the total capacity available divided by the number of periods. The actual capacity available for each period is equal to the average period capacity as a fixed constant.

*Maximum natural ordering cycle* (T): Inventory carrying cost and production set-up cost/ordering cost are two major cost parameters in MPS settings. In a single-level uncapacitated system, Sridharan et al. (1987, 1988) fixed the holding cost at $1 per unit per period, and changed the production set-up costs to have different natural ordering cycles. A similar method is also used in this study. 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 the testing problems. In multi-item single-level systems, although complete enumeration of all possible combinations of natural ordering cycles for

different items may be of interest, it is not very practical because of the combination problem. Without loss of generality, the natural ordering cycle for item 1 is assumed to be the maximum cycle among all items. The set-up cost for item 1 is varied so that the natural ordering cycle for this item (T) is 4 and 8 periods, respectively. The set-up 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 are fixed for all testing problems. Table 3 shows the cost parameters generated using this procedure.

*Unit shortage cost* (SC). In this simulation experiment, shortages can occur as a result of insufficient capacity in certain periods during any replanning cycle. Whenever capacity is insufficient to meet demand for all items, demand that cannot be met will become loss of sales. An SC parameter is used to reflect loss of profit and the negative effect on future sales. The SC for an item is assumed to be certain proportion of the unit value of the item. Assuming a period is a day and the unit holding cost per year (365 days) of an item is 25% of the unit value, the unit value for an item is 365/25% (= 1460) times of the unit holding cost per period for the item. For example, the unit holding cost per period for item 1 is $1.00, so the unit value of item 1 is $1460. In this study, the SC

is set at 10%, 20% and 40% of the item value for the low, medium and high levels of shortage costs, respectively. The values of the SC are also shown in Table 3.

### 3.2.2. Parameters for freezing the MPS

*Planning horizon* (PH). Previous research has found that the performance of the MRP system is improved when the PH is a multiple of the natural ordering cycle (Carlson et al., 1982; Blackburn and Millen, 1980). Zhao et al. (2001) found that the PH had a significant impact on total cost and instability under deterministic demand. In this study, to reduce the number of combinations of independent variables, the PH is set at four and eight times of $T$, respectively.

*Freezing proportion* (FP). FP has been found to significantly influence the performance of multi-level MRP systems. The FP is set at 0.00, 0.25, 0.50, 0.75 and 1.00, respectively, in this study. An FP of 0.00 means that the frozen interval is equal to one period and the replanning is done in every period. This case is used as a benchmark for evaluating the performance of FP.

*Replanning periodicity* (RP). RP refers to the time periods between replanning cycles. Zhao et al. (2001) found that an RP equal to the frozen interval resulted in the best system performance under deterministic demand. However, we do not know if this is also true under demand uncertainty. Therefore, the RP is set at 0.25, 0.50, 0.75 and 1.00 times of the frozen interval, respectively, in this study.

### 3.3. Dependent variables

The following three criteria will be used as the dependent variables of the experimental design.

*Total cost* (TC), which is the sum of the production set-up cost, inventory carrying cost and the shortage cost for all items within the length of the simulation run.

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

$$I = \frac{\sum_{i=l}^{n} \sum_{k>1} \sum_{t=M_k}^{M_k+N-1} |Q_{ti}^k - Q_{ti}^{k-1}|}{S}, \qquad (4)$$

where $I$ is the item index; $n$ the total number of items; $t$ the time period; $k$ the planning cycle; $Q_{ti}^k$

the scheduled order quantity for item $i$ in period $t$ during planning cycle $k$; $M_k$ the beginning period of planning cycle $k$; $N$ the length of planning horizon; $S$ the 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 system.

*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 analysed using analysis of variance (ANOVA) procedure to test the hypotheses presented in the next section.

## 4. Research hypotheses

Two general hypotheses are tested in this study:

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

**Hypothesis 2.** 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.

Hypothesis 1 is concerned with the impact of the MPS freezing parameters on system performance. Although several researchers (Sridharan et al., 1987, 1988; Sridharan and Berry 1990a, b; Sridharan and LaForge, 1990, 1994) have studied the impact of MPS freezing parameters on the performance of single-level production systems in environment of unlimited capacity, Zhao et al. (2001) have shown that some of the conclusions

cannot be generalized into the environment with capacity constraint under deterministic demand. This study will extend the study by Zhao et al. (2001) from the case of deterministic demand to the case of demand uncertainty under a single resource constraints. We expect to find that the performance of the MPS freezing parameters under demand uncertainty will be different from that under deterministic demands.

As discussed in Section 1, since one critical resource often limits the production output of a company and the master production scheduler often focuses on this critical resource in developing the master production schedule, the result of testing Hypothesis 1 under a single resource constraint is of significant academic and practical value. Furthermore, since the master production scheduler often focuses on the aggregate requirement of the critical resource in developing the master production schedule, the findings from the single-level system in this study will also have significant managerial implications for multi-level MRP systems.

Hypothesis 2 is concerned with the impact of environmental factors (CT, DV, MV, $T$, SC) on the selection of the MPS freezing parameters. The capacity tightness can significantly influence the impact of MPS freezing parameters on system performance. When the capacity is tight, freezing a larger proportion of the MPS may lead to lower utilization of the critical resources and subsequently higher shortage cost. When the capacity is not very tight, this effect will be less pronounced. When multiple products are produced using the same critical resource, both the variation in the total demand and the variation in the proportion of the demand for individual product can influence how the MPS parameter influences the performance of the system. Therefore, we also would like to examine how DV and MV will influence the selection of the MPS freezing parameters. Lastly, we also would like to investigate how the cost parameters ($T$ and SC) will influence the selection of the MPS parameters because the cost implications of MPS freezing will be quite different under different cost structures. Testing this hypothesis will allow us to see whether the environmental factors significantly influence the performance of

MPS freezing parameters. Through statistical analyses, we hope to develop guidelines for selecting MPS freezing parameters under different operation conditions.

## 5. Results

In order to test the above hypotheses, the simulation output was analysed using the ANOVA procedure. The residual analysis using SAS suggests that the data violates the assumption of constant variance and suggests the logarithm transformations for TC, SI and square transformation of SL. Table 4 shows the main and two-way interaction effects of the independent variables for each of the dependent variables using the transformed data.

Examination of the results in Table 4 shows that most of the main and two-way interaction effects are significant in influencing TC, SI and SL at 5% significance level. To examine the impact of the independent variables on the dependent variables, Duncan's multiple-range test was performed to rank the performance of MPS freezing parameters. In order to get more managerial insights, we used the original non-transformed data in the following analyses and discussions. The results are presented around the hypotheses shown in Section 4.

### 5.1. Overall performance of MPS freezing parameters

The ANOVA results in Table 4 show that the main effects of all three MPS freezing parameters (PH, FP and RP) significantly influence TC, SI and SL at 5% significance level. To compare the performance of the freezing parameters, the relative total costs (RTC), the relative schedule instabilities (RSI) and the service levels using different MPS freezing parameters are shown in Table 5. The RTC and the RSI are calculated by dividing the lowest TC and the lowest SI (setting to 100 as benchmark) into the TC and SI for a specific parameter value. To examine the impact of the freezing parameters on system performance, the performance of each MPS freezing parameter is ranked using Duncan's multiple range tests and

Table 4
Selected ANOVA results

| Dependent variables | | TC[a] | | SI[b] | | SL[c] | |
|---|---|---|---|---|---|---|---|
| Source | DF | $F$ value | $Pr > F$ | $F$ value | $Pr > F$ | $F$ value | $Pr > F$ |
| DV | 2 | 87731.83 | 0.0001 | 7956.28 | 0.0001 | 68640.87 | 0.0001 |
| MV | 2 | 97152.27 | 0.0001 | 19962.54 | 0.0001 | 80773.39 | 0.0001 |
| DV∗MV | 4 | 5233.33 | 0.0001 | 995.19 | 0.0001 | 1119.81 | 0.0001 |
| CT | 2 | 14217.47 | 0.0001 | 99999.99 | 0.0001 | 4373.99 | 0.0001 |
| DV∗CT | 4 | 245.30 | 0.0001 | 4568.50 | 0.0001 | 104.06 | 0.0001 |
| MV∗CT | 4 | 598.05 | 0.0001 | 5294.03 | 0.0001 | 21.87 | 0.0001 |
| SC | 2 | 99999.99 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| DV∗SC | 4 | 509.39 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| MV∗SC | 4 | 680.50 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| CT∗SC | 4 | 24.65 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| $T$ | 1 | 720.77 | 0.0001 | 99999.99 | 0.0001 | 23805.47 | 0.0001 |
| DV∗T | 2 | 1130.72 | 0.0001 | 168.24 | 0.0001 | 478.04 | 0.0001 |
| MV∗T | 2 | 1705.32 | 0.0001 | 2.67 | 0.0690 | 584.06 | 0.0001 |
| CT∗T | 2 | 2174.17 | 0.0001 | 6793.89 | 0.0001 | 138.48 | 0.0001 |
| $T$∗SC | 2 | 5463.46 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| PH | 1 | 3228.93 | 0.0001 | 7216.42 | 0.0001 | 3942.72 | 0.0001 |
| DV∗PH | 2 | 4.29 | 0.0138 | 4.86 | 0.0078 | 72.40 | 0.0001 |
| MV∗PH | 2 | 2.04 | 0.1300 | 3.28 | 0.0378 | 68.39 | 0.0001 |
| CT∗PH | 2 | 7.67 | 0.0005 | 587.26 | 0.0001 | 29.69 | 0.0001 |
| SC∗PH | 2 | 93.07 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| $T$∗PH | 1 | 595.36 | 0.0001 | 822.54 | 0.0001 | 292.71 | 0.0001 |
| FP | 3 | 7517.95 | 0.0001 | 99999.99 | 0.0001 | 4345.95 | 0.0001 |
| DV∗FP | 6 | 172.60 | 0.0001 | 101.15 | 0.0001 | 64.50 | 0.0001 |
| MV∗FP | 6 | 164.69 | 0.0001 | 48.73 | 0.0001 | 316.29 | 0.0001 |
| CT∗FP | 6 | 1296.05 | 0.0001 | 1104.79 | 0.0001 | 723.44 | 0.0001 |
| SC∗FP | 6 | 99.36 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| $T$∗FP | 3 | 2522.37 | 0.0001 | 9917.67 | 0.0001 | 1380.63 | 0.0001 |
| PH∗FP | 3 | 166.06 | 0.0001 | 8948.91 | 0.0001 | 194.70 | 0.0001 |
| RP | 3 | 4303.79 | 0.0001 | 43576.86 | 0.0001 | 3688.24 | 0.0001 |
| DV∗RP | 6 | 13.11 | 0.0001 | 5.86 | 0.0001 | 58.94 | 0.0001 |
| MV∗RP | 6 | 5.86 | 0.0001 | 12.71 | 0.0001 | 108.09 | 0.0001 |
| CT∗RP | 6 | 13.13 | 0.0001 | 186.08 | 0.0001 | 0.63 | 0.7043 |
| SC∗RP | 6 | 32.22 | 0.0001 | 0.00 | 1.0000 | 0.00 | 1.0000 |
| $T$∗RP | 3 | 28.13 | 0.0001 | 226.48 | 0.0001 | 79.12 | 0.0001 |
| PH∗RP | 3 | 253.98 | 0.0001 | 7.99 | 0.0001 | 205.13 | 0.0001 |
| FP∗RP | 9 | 525.37 | 0.0001 | 4849.96 | 0.0001 | 435.55 | 0.0001 |

[a] Based on residual analysis and suggestions by SAS, log transformation of TC (i.e., $\log_{10}$(TC)) was made to satisfy the assumptions of ANOVA.

[b] The observations for FP = 1.0 were not included in the analysis because SI is always equal to zero when FP = 1.0. Based on residual analysis and suggestions by SAS, log transformation of SI (i.e., $\log_{10}$(SI)) was made to satisfy the assumptions of ANOVA.

[c] Based on residual analysis and suggestions by SAS, square transformation of SL (i.e., $SL^2$) was made to satisfy the assumptions of ANOVA.

are also shown in Table 5. Comparison of the results in Table 5 with those reported by previous studies under no capacity constraints or deterministic demand is summarized in Table 6. These results are discussed below.

### 5.1.1. Impact of planning horizon

Table 5 shows that a PH of eight times of $T$ results in a lower TC, a higher SL, and a higher SI than a PH of four times of $T$. Therefore, a longer planning horizon will help to improve total cost

Table 5
Overall performance of MPS freezing parameters

| Independent variables | Values | Dependent variables | | | | | |
|---|---|---|---|---|---|---|---|
| | | Total cost | | Schedule instability | | Service level | |
| | | RTC[a] | RANK[b] | RSI[c] | RANK[b] | SL[d] | RANK[b] |
| Planning horizon (PH) | 4 | 106 | 2 | 100 | 1 | 93.04 | 2 |
| | 8 | 100 | 1 | 168 | 2 | 93.61 | 1 |
| Freezing proportion (FP) | 0.00 | 100 | 1 | 4667 | 5 | 94.17 | 1 |
| | 0.25 | 130 | 5 | 865 | 4 | 92.39 | 5 |
| | 0.50 | 122 | 4 | 296 | 3 | 93.04 | 4 |
| | 0.75 | 117 | 3 | 100 | 2 | 93.43 | 3 |
| | 1.00 | 116 | 2 | 0 | 1 | 93.62 | 2 |
| Replanning periodicity (RP) | 0.25 | 118 | 4 | 131 | 4 | 92.70 | 4 |
| | 0.50 | 112 | 3 | 111 | 3 | 93.11 | 3 |
| | 0.75 | 107 | 2 | 104 | 2 | 93.51 | 2 |
| | 1.00 | 100 | 1 | 100 | 1 | 93.99 | 1 |

[a] RTC represents relative total cost. For each independent variable, the lowest total cost among all its values is set at 100. The relative total costs 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 obtained using Duncan's multiple range test with significance level of 5%.

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

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

and service level performance of the system, but will lead to higher schedule instability. Managers will have to make trade-offs between total cost and service level on the one hand and the schedule instability on the other in selecting the proper planning horizon. These results agree with the findings by Zhao et al. (2001) under a single resource constraint and deterministic demand. Therefore, the existence of the demand uncertainty did not change the conclusion concerning the im-pact of planning horizon on system performance.

The results concerning the performance of PH in this study under capacity constraint and demand uncertainty are compared with those of previous studies in Table 6. The instability result is almost the same as that under capacity constraint and deterministic demand reported by Zhao et al. (2001) and that under demand uncertainty without considering capacity constraint reported by Sridharan and Berry

(1990b). Therefore, neither the introduction of the demand uncertainty nor the capacity constraint changes the relative performance of PH according to schedule instability. However, the relative total cost performance of PH under capacity constraint and demand uncertainty observed in this study is quite different from that under demand uncertainty without considering capacity constraint observed by Sridharan and Berry (1990a). While a longer planning horizon reduces total cost under capacity constraint, it increases total cost when no capacity constraint is considered. The different performance of PH observed in these two simulations was caused by the capacity constraint. Under a capacity constraint, a longer PH will allow for more opportunities to make MPS adjustments to better utilise the capacity. These opportunities reduce infeasibility caused by limited capacity, thus leading to higher service levels, lower costs and higher schedule instability. The higher service level

Table 6
Comparison of the overall performance of MPS freezing parameters

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

[a] The references: SBU, 1987: Sridharan et al. (1987); SBU, 1988: Sridharan et al. (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 et al. (2001).

[b] "⇑" means "increase", "⇓" means "decrease", "X" means "remain almost the same", and "N/A" means "not applicable".

[c] "WW" means using Wagner–Whitin lot-sizing rule and "SM" means using silver-meal lot-sizing rule.

associated with the longer PH shown in Table 5 reflects this fact.

### 5.1.2. Impact of freezing proportion

The relative performance of the FP is shown in Table 5 and also plotted in Fig. 3. The total cost is the lowest when FP = 0 (i.e., frozen interval of only one period). The vertical scale indicates the relative total cost, which is equal to the absolute total cost of the system divided by the lowest total cost (the cost for FP = 0) multiplied by 100. The service level is the total percentage of demand satisfied in percentage terms. When FP = 0, the service level is the highest. When FP = 0.00, only the order generated by the lot-sizing rule in the first period is frozen. Since the basic objective of the lot-sizing rule (DS) is to lump some periods' requirements to save cost based on the trade-off of production set-up cost and inventory carrying cost, the order generated by the lot-sizing rule (DS) in the first period is usually greater than the forecasted net requirement in this period. Therefore, freezing the

order in the first period usually will not result in loss of sale in this period even when the realised demand for this period exceeds the forecast. Furthermore, if there is excess capacity in other periods of this replanning cycle, it can be used in the next replanning cycle when new forecast information becomes available as all, but the first one, orders in the entire planning horizon can be changed in the next replanning cycle. That is why FP = 0.00 results in the highest service level and the lowest total cost among all the freezing proportions.

When FP is non-zero (0.25, 0.50, 0.75 and 1.00), however, a lower FP performs worse than a higher FP. There are two factors that influence the performance of the freezing proportion. On the one hand, when FP is lower, if there is excess capacity in non-frozen periods of this replanning cycle, it can be used in the next replanning cycle, therefore, there is a possibility to make better use of the capacity and to produce higher service level.
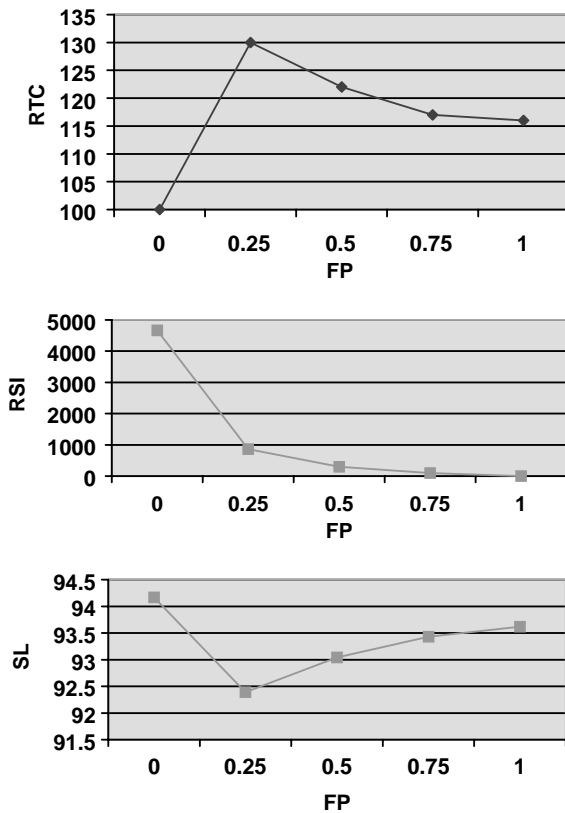
Fig. 3. Overall performance of freezing proportion.

fact that some periods may have higher level of stocks to be used in later periods. Furthermore, a lower FP calls for more replanning cycles to complete the entire simulation run, thus produces more chances for shortages at the frozen intervals of the replanning cycles. Therefore, a lower FP performs worse than a higher FP when FP is non-zero (0.25, 0.50, 0.75 and 1.00) according to TC and SL.

Fig. 3 also indicates that a higher FP results in a lower SI. When FP is equal to 1.00, the entire planning horizon is frozen so that no order changes can occur, thus SI is zero. The vertical scale for the schedule instability chart indicates the relative instability using the schedule instability for FP = 0.75 as the benchmark (set at 100). The relative instability for other proportions is obtained by dividing the instability of the benchmark into the schedule instability of the freezing proportion, then multiplied by 100. The finding concerning the SI performance of FP agree with the findings of Sridharan et al. (1988) and Sridharan and Berry (1990a, b) without considering capacity constraints and that of Zhao et al. (2001) considering capacity constraints under deterministic demand.

Based on the above results, we can make some managerial implications for the selection of freezing proportion. If a company mainly considers total cost and service level in selecting FP, FP should be set at 0. If the company also want to reduce SI, it should use a FP of 1.00. To select a proper FP under capacity constraint, only very small FP and very large FP should be considered based on the trade-off between TC, SL and SI.

The findings concerning the TC performance of FP disagrees with the findings by Sridharan et al. (1987) and Sridharan and Berry (1990a, b) without considering capacity constraints and that by Zhao et al. (2001) considering capacity constraints under deterministic demand. In their studies, they have found that TC increases when FP increases. These differences are caused by the combination of demand uncertainty and capacity constraints.

### 5.1.3. Impact of replanning periodicity

The relative performance of RP (expressed as a fraction of the frozen interval) is also shown in

On the other hand, there are also disadvantages of using a lower FP under demand uncertainty. In this study, there are no trend or seasonal fluctuations in demands, thus the forecast produced by the forecasting model (moving average) is unbiased and the total forecasted requirements are usually very close to the total actual demands for the entire planning horizon. Even the realised demands may exceed the forecasts in some period and shortage may occur, in other periods forecasts may exceed the actual demand and excess stocks in these periods can be used to satisfy demands for other periods. The possibility of shortage in the earlier periods (except the first few periods which are definitely covered by the first production order) of the planning horizon is usually higher than that in the later periods because of the possibility that some later periods will have excess stocks. Therefore, a longer freezing proportion may result in higher level of services because of the

Table 5. Examination of Table 5 indicates that a higher RP results in a lower TC, a higher SL and lower SI. Therefore, it is more beneficial to replan less frequently. The system achieves the best performance when replannings are carried out after the entire frozen interval has passed (RP = 1.0). A similar relationship between TC, SI and RP is also found by Sridharan and Berry (1990a, b) without considering capacity constraints and Zhao et al. (2001) under capacity constraints and deterministic demand.

The findings that less frequent replanning improves performance can be explained by the fact that more frequent replanning can cause excessive changes in the MPS. The more frequent are the replanning activities, the less additional demand information will become available to the planner when the planner moves from one replanning cycle to another. Furthermore, the changes in the demand forecasts in successive replanning cycles will mostly be caused by the random variations in the demand, and thus the resulting changes in the MPS do not really help to improve service level. However, excessive changes in the MPS may result in extra production set-ups and increases in inventories in some periods. Some of these suboptimal changes will be frozen and therefore cannot be revised even when additional demand forecasts become available in future periods. As a result, more sub-optimal ordering decisions will be implemented under more frequent replanning, leading to worse system performance.

In summary, the results in Table 5 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 6 shows that some conclusions from studies under no capacity constraints can be generalized to the case of having a single resource constraint while others will not hold under capacity constraints. When the findings from the case of single resource constraint under deterministic demand are compared with those under demand uncertainty, the only conclusion that is different is the performance of the freezing

proportion. While a higher freezing proportion always results in higher total cost and a lower service level under deterministic demand, a freezing proportion of 0 always results in the lowest cost and the highest service level among the four freezing proportions.

## 5.2. Impact of environmental factors on performance of MPS freezing parameters

From the results in Table 4, we can see that all two-way interactions (except MV∗PH) between MPS freezing parameters and the environmental factors (CT, DV, MV, $T$ and SC) significantly influence TC at 5% significance level. All interactions between MPS freezing parameters and the environment factors except SC also significantly influence SI. For SL, all interactions (except CT∗RP) between MPS freezing parameters and the environment factors except SC are also significant. In order to examine the impacts of the environmental factors on the performance of the MPS freezing parameters, Duncan's multiple-range test was performed to rank the performance of MPS freezing parameters under different values for each environmental factor. However, the results show that most of them do not influence the relative performance ranking of the MPS freezing parameters. In order to save space, only results for capacity tightness (CT) are presented here.

The performance of MPS freezing parameters under different CT values is shown in Table 7. The major findings from Table 7 are summarised below:

(1) The performance of PH: Under different CT conditions, the relative performance rankings of different PH values are the same in terms of all three criteria. Furthermore, the differences in TC and SL between PH = 4 and 8 are almost the same under all CT conditions. However, the difference in SI between different planning horizons decreases as the capacity becomes tighter. As capacity constraint becomes tighter, there are fewer opportunities to change production schedule made in previous replanning cycles because there is little excessive capacity. Therefore, the difference in SI between different PH values decreases.

Table 7
Performance of MPS freezing parameters under different capacity tightness

| Dependent variables | | Total cost | | Schedule instability | | Service level | |
|---|---|---|---|---|---|---|---|
| Independent variables | | RTC[a] | RANK[b] | RSI[c] | RANK[b] | SL[d] | RANK[b] |
| CT = low | PH = 4 | 106 | 2 | 100 | 1 | 93.54 | 2 |
| | PH = 8 | 100 | 1 | 175 | 2 | 94.02 | 1 |
| | FP = 0.00 | 100 | 1 | 5099 | 5 | 95.41 | 1 |
| | FP = 0.25 | 152 | 5 | 920 | 4 | 92.76 | 5 |
| | FP = 0.50 | 144 | 4 | 312 | 3 | 93.29 | 4 |
| | FP = 0.75 | 138 | 3 | 100 | 2 | 93.66 | 3 |
| | FP = 1.00 | 137 | 2 | 0 | 1 | 93.81 | 2 |
| | RP = 0.25 | 120 | 4 | 130 | 4 | 93.18 | 4 |
| | RP = 0.50 | 114 | 3 | 111 | 3 | 93.55 | 3 |
| | RP = 0.75 | 108 | 2 | 104 | 2 | 93.96 | 2 |
| | RP = 1.00 | 100 | 1 | 100 | 1 | 94.45 | 1 |
| CT = medium | PH = 4 | 106 | 2 | 100 | 1 | 93.15 | 2 |
| | PH = 8 | 100 | 1 | 163 | 2 | 93.71 | 1 |
| | FP = 0.00 | 100 | 1 | 4752 | 5 | 94.34 | 1 |
| | FP = 0.25 | 133 | 5 | 878 | 4 | 92.42 | 5 |
| | FP = 0.50 | 125 | 4 | 297 | 3 | 93.10 | 4 |
| | FP = 0.75 | 119 | 3 | 100 | 2 | 93.53 | 3 |
| | FP = 1.00 | 118 | 2 | 0 | 1 | 93.75 | 2 |
| | RP = 0.25 | 118 | 4 | 131 | 4 | 92.80 | 4 |
| | RP = 0.50 | 113 | 3 | 111 | 3 | 93.21 | 3 |
| | RP = 0.75 | 107 | 2 | 104 | 2 | 93.62 | 2 |
| | RP = 1.00 | 100 | 1 | 100 | 1 | 94.09 | 1 |
| CT = high | PH = 4 | 107 | 2 | 100 | 1 | 92.44 | 2 |
| | PH = 8 | 100 | 1 | 157 | 2 | 93.10 | 1 |
| | FP = 0.00 | 100 | 1 | 3439 | 5 | 92.76 | 3 |
| | FP = 0.25 | 112 | 5 | 705 | 4 | 92.00 | 5 |
| | FP = 0.50 | 105 | 4 | 252 | 3 | 92.72 | 4 |
| | FP = 0.75 | 102 | 3 | 100 | 2 | 93.08 | 2 |
| | FP = 1.00 | 101 | 2 | 0 | 1 | 93.29 | 1 |
| | RP = 0.25 | 116 | 4 | 130 | 4 | 92.14 | 4 |
| | RP = 0.50 | 111 | 3 | 111 | 3 | 92.56 | 3 |
| | RP = 0.75 | 106 | 2 | 104 | 2 | 92.96 | 2 |
| | RP = 1.00 | 100 | 1 | 100 | 1 | 93.43 | 1 |

[a] RTC represents relative total cost. The lowest total cost is set at 100. The relative total costs of the other capacity tightness are obtained by dividing the lowest total cost into the total costs of the specific conditions.

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

[c] RSI represents relative schedule instability. The lowest schedule instability among all its values is set at 100. The relative schedule instabilities of the other capacity tightness are obtained by dividing the lowest schedule instability into the schedule instabilities of the specific conditions.

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

(2) The performance of FP: Under different CT conditions, the relative performance rankings of different FP values are the same in terms of TC and SI. However, the differences in TC and SI between FP = 0.00 and non-zero FP values decrease significantly when capacity becomes tighter. Furthermore, according to SL, the relative ranking of different FP values are different under different CT values. When CT is low or medium, FP = 0.00 produces the

highest service level, while FP = 1.00 produces the highest service level when CT is high. Under capacitated system with demand uncertainty, the losses of sales usually occur in the earlier periods of a replanning cycle if all planned orders are implemented. A larger FP reduces the number of total replanning cycles, thus leading to higher service level and lower total cost. However, when capacity is not high, the service level under FP = 1.00 is lower than that under FP = 0.00, because FP = 0.00 incurs replanning at every period and thus has more chance to make better use of the capacity and to adjust the order to fill in the actual demand. When capacity constraint becomes tighter, the possibility of shortage also becomes higher, thus more benefits can be obtained through a larger FP. Therefore, freezing up to 75–100% of the whole planning horizon produces higher service level than freezing only one period. It is interesting to notice that, although FP = 1.0 produces highest service level when CT is high, the total cost produced by FP = 1.0 is still higher than that produced by FP = 0.00. This is because substantially higher inventory cost occurs when FP = 1.0. While the decreased number of replanning cycles when FP = 1.0 helps to improve the service level and reduce the total shortage cost, it also increases the amount of inventory in the system under tight capacity. This inventory cost increase dominates the decrease in shortage cost.

(3) The performance of RP: Under different CT conditions, the relative performance rankings of different RP values are the same in terms of all three criteria. However, when capacity constraint becomes tighter, the difference in TC between different RP values becomes smaller (from 20% for CT = low to 16% for CT = high), but the differences in SI and SL between different RP values remain almost unchanged when the capacity tightness is changed. A higher RP rolls the schedule forward for more periods in each replanning cycle and more additional forecasted demand information will become available, thus leading to better performance. When capacity

tightness is high, the limited excess capacity reduces the opportunity to make better use of the more forecasted demand information under a larger RP. Therefore, the difference in TC between different RP values decreases when capacity becomes tighter.

Overall, the results in Table 7 support research Hypothesis 2 as it relates to CT. However, most of the relative performance rankings of the freezing parameters remain the same under different CT values. The only exception is that CT influences the relative rankings of FP parameter in terms of service level criteria.

## 6. Discussions and conclusions

This study extends earlier studies of freezing the MPS from a single end-item system without any capacity constraints to a multiple end-item system with a single resource capacity constraint under demand uncertainty. This paper investigates the impact the parameters for freezing the MPS on the total cost, schedule instability and service level of multi-item single-level systems with a single resource constraint. It also examines the impact of cost structure and capacity tightness on the selection MPS freezing parameters under rolling time horizons and demand uncertainty. Through comprehensive computer simulation and statistical analyses, we find the following:

(1) The length of the planning horizon, the freezing proportion and the RP all significantly influence the total cost, schedule instability and service level in multi-item single-level systems under demand uncertainty. To select the proper freezing proportion and planning horizon, trade-offs between total cost, service level and schedule instability have to be made while the longest RP always results in the best performance according to all three performance measures.

(2) Some conclusions under no capacity constraints or deterministic demand are also true under capacity constraints and demand uncertainty. However, some others are

significantly different from those without capacity constraints or under deterministic demand. For example, the impact of the RP on system performance is the same regardless of whether the capacity constraint exists. However, the impacts of planning horizon and the freezing proportion are influenced by the existence of the capacity constraint. Therefore, it is important for the master production scheduler to consider the capacity constraint when selecting the proper parameters for freezing the master production schedule.

(3) Most of the two-way interactions between MPS freezing parameters and the environmental factors significantly influence the performance of the system. Although the environmental factors do not influence most of the relative performance rankings of the PH and RP parameters, the relative performance ranking of the FP parameter in terms of service level can be influenced by some environmental factors such as capacity tightness.

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 impact of freezing the MPS under capacity constraints and demand uncertainty.

Although the study makes a significant contribution to the academic literature and to practical application, it also has several limitations. 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 insights to the problem, more insights 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, lot-sizing rules and other factors will be very complex. Investigation of these interaction effects on MRP system performance should provide further insights 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. In this study, we assumed that there are no seasonality and trends in the demand patterns and only the moving average model is used. It will be interesting to examine the impact of demand patterns and forecasting models on the selection of MPS freezing parameters under different operating conditions.

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