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Comparing dynamic risk-based scheduling methods with MRP via simulation.

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COMPARING DYNAMIC RISK-BASED SCHEDULING METHODS WITH MRP VIA SIMULATION

By

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VIA SIMULATION

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ABSTRACT

COMPARING DYNAMIC RISK-BASED SCHEDULE METHODS WITH MRP VIA SIMULATION

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Material Requirements Planning (MRP) is one of the earliest production scheduling approaches that utilizes computers. MRP is still regarded as one of the most widely used systems for production scheduling. Even though MRP has made contributions, there are some fundamental problems (i.e. the assumption of infinite capacity and fixed lead times) which make the MRP system vulnerable to effects of uncertainty. To overcome this fundamental flaw, there was a trend towards the development of detailed finite-capacity scheduling systems (i.e. MRP II, ERP, and APO). All these MRP-based systems still ignore variability and randomness and are inherently push systems.

Instead of creating a detailed schedule based on forecast, Factory Physics Inc. developed Dynamic Risk-Based Scheduling (DRS), which creates a set of policy parameters (e.g. WIP level, lot sizes, reorder point, and reorder quantity) that work for a range of situations to calculate the production schedule.

This thesis compares the key performance measures of DRS and MRP-based scheduling systems. We begin with a single-machine problem and develop simulation models for varying levels of uncertainty in forecast demand (i.e. base demand scenario, under-estimated scenario and over-estimated scenario) and two levels of variability in the system (i.e. moderate variability and no variability). Then the experiment is extended to multiple-machine problems. We also introduce more constraints into the DRS and MRP models to improve their performance. We also test the performance of MRP models for different planning horizons. We find that the DRS strategy is more robust to forecast error than MRP-based strategies. DRS also usually obtains better performance than MRP-based models in terms of higher fill rate and lower inventory.

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CHAPTER 1 INTRODUCTION

In this thesis, we compare the traditional MRP-based strategies with a new production scheduling strategy named as Dynamic Risk-based Scheduling (DRS) developed by Factory Physics Inc.

1.1 Background

Manufacturing systems strive to achieve multiple objectives such as meeting deliveries on-time, minimizing work-in-process inventory, shortening customer lead times, and maximizing resource utilization, which often conflict. For example, it is easier to finish jobs on time when utilization of resources is low. Customer lead times can be shortened if a large inventory is maintained. The goal of production scheduling is to strike a profitable balance among these conflicting objectives (Hopp and Spearman 2008).

Scheduling as a practice is as old as manufacturing itself. It did not start as a research discipline until the scientific manufacturing movement in the early 1900s. But serious analysis of scheduling problems did not begin until the development of the computer in the 1960s and 1970s. MRP is one of the earliest production scheduling approaches based on the application of computers. Although it started slowly, MRP got an extensive development in 1972 because the American Production and Inventory Control Society (APICS) launched its "MRP Crusade" to promote its use (Hopp and Spearman 2008). MRP is still regarded as one of the most widely used systems for production scheduling

(Mohan and Ritzman 1998). Even though MRP has made contributions, there are some fundamental problems (i.e. the assumption of infinite capacity and fixed lead times) which make the MRP system vulnerable to effects of uncertainty. To overcome this fundamental flaw, there was a trend toward the development of more and more detailed finite-capacity scheduling systems (i.e. MRP II, ERP, and APO). All these are still MRP-based systems which ignore variability and randomness and are thus inherently push systems.

Instead of creating a detailed schedule based on forecast, Factory Physics Inc. developed Dynamic Risk-Based Scheduling (DRS), which creates a set of policy parameters (e.g. WIP level, lot sizes, reorder point, and reorder quantity) that work for a range of situations to calculate the production schedule. The policy is dynamic, which means that it depends on the actual demand and the actual production. The policy is risk-based, which means that it considers random events and assumes inaccuracy in the forecast. The optimal execution obtained from DRS policy results in a manufacturing system that is robust enough to accommodate moderate changes in demand and/or capacity without the need to reschedule. It also can detect when the assumption regarding demand and capacity used to determine the dynamic policy is no longer valid and indicates the need for either more or less capacity.

1.2 Problem statement

This thesis compares the key performance measures (fill rate, inventory, backorder, etc) in manufacturing systems between DRS and MRP-based systems. The objective is to demonstrate the conditions under which static models may be preferred and conditions under which dynamic models may be preferred via simulation and analytical tools.

We develop simulation models for all the policies and compare the performance measures under different scenarios. We compare the performance of the models for varying levels of uncertainty in demand forecasts and two levels of variability in systems. We also compare the simulation results with analytical models to demonstrate the validity of the analytical models.

By comparing the model performance under different scenarios, we not only estimate which policy is better under a specific situation, we also find the impact of uncertainty and variability in the systems for different policies.

1.3 Thesis organization

Chapter 2 provides a review of the literature associated with various production scheduling models. Chapter 3 focuses on the introduction of the production scheduling models we compare (i.e. MRP and DRS). Chapter 4 discusses the development of simulation models of all the systems. Chapter 5 discusses the design of experiments. We begin with a system which contains one machine and 23 parts. In this single-machine case, we compare the performance between MRP and DRS for varying levels of uncertainty in forecast demand (e.g. over-estimated forecast, under-estimated forecast). We also develop the system for two levels of variability (i.e. moderate variability and no variability) and compare the performance between MRP and DRS. Then we extend to multiple-machine cases with multiple machines and multiple products. We introduce more constraints, such as CONWIP, recourse, makespan and capacity constraints into

MRP and DRS models to improve their performance. Chapter 6 summarizes the conclusion of this thesis.

CHAPTER 2 LITERATURE REVIEW

In this chapter we review literature associated with the production scheduling problem as well as the comparison between different scheduling policies.

2.1 Production scheduling in a push environment

During the 1960s, Joseph Orlicky, Oliver Wight and others developed Material Requirements Planning (MRP). The basic idea is that a production schedule of an end item translates into known quantity and timing needs of components based on demand requirements, bill-of-material and lead time information (Orlicky 1975).

The terms "push" and "pull" have been widely used to describe manufacturing systems. MRP is called a push system because it computes schedules of what should be started (or pushed) into production based on demand (Hopp and Spearman 2008).

Although MRP started slowly, it got an extensive development in 1972 because the American Production and Inventory Control Society (APICS) launched its "MRP Crusade" to promote its use (Hopp and Spearman 2008). Orlicky reported 150 implementations in 1971 (Orlicky 1975). By 1981, the number of implementations had increased to around 8,000 (Wight 1995).

However, the success of MRP is not spotless, and there are some fundamental problems (i.e. infinite capacity and fixed lead times assumptions) which make the MRP system vulnerable to the effects of uncertainty. There is a conflict between MRP's deterministic nature and the uncertainty of most operations. The inherent assumption in an MRP system is that the actual production parameters such as lot size and delivery lead-time are fixed, which can be rarely achieved in practice. In reality, especially in the job-shop environment, actual lead time and optimal lot sizes are neither known nor fixed (Karmarkar 1989).

It is difficult for the MRP system to deal with the uncertainty inherent in most operations. Small parameter changes at the final assembly level often causes large changes at earlier production levels, which is called "MRP nervousness" (Krupp 1984). Uncertainty in the timing or quantity of demand can exacerbate the nervousness. In addition, uncertainty in the filling of orders, or variations in the quantity produced or lead time, can be another source of nervousness (Blackburn et al. 1986).

Many dampening methods have been proposed to reduce system nervousness in order to minimize its negative impact on production systems. Introduction of safety stock and safety lead time is a widely used method dealing with the uncertainty in the system (Blackburn et al. 1986). Whybark and Williams (1976) built a simulation model to compare the performance of safety stock and safety lead time, which build a buffer inventory to protect against demand uncertainty. The results have concluded that safety stock is preferable to safety time for buffering against quantity uncertainty, while the safety lead time is more appropriate in the case of time uncertainty. Their research provides a general guideline for choosing between two buffering methods in an MRP system.

Forecast error is an important factor that affects the performance of an MRP system. Lee and Adam (1986) conducted a simulation study to examine two dimensions of forecast error: standard deviation and bias. They found that standard deviation is relatively less important in terms of the magnitude of the total cost impact, which includes inventory carrying cost, setup cost and end-item shortage cost. Their results suggest that higher forecast error level may not result in higher total cost, which seems to contradict what we intuitively believe. The lot-for-lot rule resulted in the least total coast at a significant positive bias forecast error. Even for other lot-sizing rules, a slight bias (positive or negative) may also improve MRP performance.

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

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

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

1) Allowing purchase parts to arrive late more frequently than allowing them to arrive early would be advantageous because it results in the lowest total costs of the system;
2) When buffering against uncertainty of the supply/timing variety, it is more prudent to use safety stock instead of safety lead time. This conclusion contradicts the finding from Whybark and Williams (1976), who suggested that safety stock is more appropriate for buffering quantity uncertainty and safety lead time for dampening timing uncertainty;
3) The lot-for-lot rule should be used when the lead time distribution of purchased parts follows the uniform discrete distribution which exhibits the most variability.

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

Mohan and Ritzman (1998) conducted a simulation study to investigate the impact of planned lead times on performance in multistage manufacturing where MRP is used in a make-to-stock environment. They found that:

1) Planned lead times are important to customer service under all operating environments, but have a less effect on inventory than factors such as lot size and product structure;
2) Tight due dates introduced by short planned times result in poor customer service without saving much inventory;
3) Small increases to planned lead times improve customer service substantially with small inventory increases;

Guide and Srivastava (2000) gave a comprehensive review of techniques of buffering against uncertainty with MRP systems. Yeung et al. (1998) reviewed important parameters which affect the effectiveness of MRP systems. They classified the literature into seven groups based on their impact on MRP performance:

1) MPS frozen interval;
2) MPS replanning frequency;
3) MPS planning horizon;

4) Product structure;
5) Forecast error;
6) Safety stock;
7) Lot-sizing rules.

The original MRP system neglected capacity constraints. It analyzed the material flow separated from capacity and routing, which is another major shortcoming (Lambrecht and Decaluwe 1988). Today MRP production schedules are usually adjusted by a bottoms-up replanning procedure which can incorporate the production capacity limit. However, this two-step procedure for determining the lot sizes under capacity is much more complex (Benton and Shin 1998).

MRP provides a systematic method to plan and procure materials to support production. However, issues such as capacity infeasibility, and system nervousness can undermine the effectiveness of an MRP system. Over time, additional procedures were developed to address some of the problems in order to improve the MRP performance. These were incorporated into a larger system called Manufacturing Resources Planning, or MRP II, which combined MRP with demand management, forecasting, capacity planning, dispatching, input/output control and other modules (Hopp and Spearman 2004). It grew in popularity, and 16 companies sold $400 million in MRP II software in 1984 alone (Zais 1986). By the end of the 1980s, Enterprise Resource Planning (ERP) was developed, which is a more advanced version of MRP II, containing modules for many business functions such as integrating sales, marketing, human resources, accounting, purchasing and logistics modules (Hopp and Spearman 2004). Of course, it was correspondingly more expensive. However, the principle deployed in ERP is MRP II when ERP is applied to production planning and scheduling with a manufacturing environment (Koh et al. 2002).

Koh et al. (2002) refer to the use of MRP, MRP II and ERP as a production planning and scheduling system within manufacturing enterprises as MRP-planned manufacture. They conclude that MRP, MRP II or ERP is an enabler (planner) rather that an optimizer (executor), which means that under a perfect manufacturing environment (without the effects of uncertainty), the plan can be executed. Otherwise, some other techniques, such as rescheduling or subcontracting, have to be applied in the planner to deal with uncertainty in the environment.

2.2 Production scheduling in a pull environment

In the 1970s and 1980s, while MRP was steadily dominating the American production system, Japan was taking an entirely different direction.

Starting in the 1940s, Taiichi Ohno began evolving a system that would enable Toyota to catch up with the American automobile industry, which is now known as the "Toyota Production System". It was designed to "make goods; as much as possible, in a continuous flow" (Ohno 1988). Ohno (1988) described the system as resting on two pillars:

1) Just-in-time (JIT), or producing only what is needed
2) Autonomation, or automation with a human touch

According to Ohno (1988), JIT involved two components: kanban and level production. Kanban or "pull production" became the hallmark of the Toyota Production System.

To describe the Toyta kanban system, Hopp and Spearman (2008) distinguish between push and pull production control systems as follows: In a push system, such as MRP, work releases are scheduled, and in a pull system, releases are authorized. The difference is that a schedule must be prepared in advance, while an authorization is decided by the status of the plant.

Huang and Kusiak (1996) summarize the main principles for the implementation of Kanban systems as:

1) Level production (balance the schedule) in order to achieve low variability of the number of parts from one time period to the next.
2) Avoid complex information and hierarchical control systems on a factory floor.
3) Do not withdraw parts without a kanban.
4) Withdraw only the parts needed at each stage.
5) Do not send defective parts to the succeeding stages.
6) Produce the exact quantity of parts withdrawn.

Kanban pull systems have been analyzed via simulation, mathematical and stochastic modeling approaches (Uzsoy and Martin-Vega 1990).

The simulation studies of kanban can be broadly classified as (Huang and Kusiak 1996):

1) Explorative analysis of pull systems
2) Comparative analysis of push and pull systems

Yavuz and Satir (1995) and Huang and Kusiak (1996) present reviews of simulation modeling.

Krajewski et al. (1987) developed a large simulation model which is able to represent diverse manufacturing environments. The results show that the kanban system, by itself, is not crucial to improve performance. The benefits of implementing a kanban system result from the manufacturing environment with uniform workflows and flexibility to adjust to changing capacity requirements.

Huang and Kusiak (1996) state that deterministic models are suitable to optimize some objective functions of the kanban system in the deterministic repetitive environment. However, it might not be appropriate in a dynamic environment. In the stochastic approach, Markov chains are often used to describe the system where the pull demand and the production time are modeled as variables. The general assumptions are the Poisson process arrivals and exponential processing time (Mitra and Mitrani 1990; Siha 1994).

The benefits of kanban in specific and pull in general have been widely cited as: (Cheng and Podolsky 1996; Hopp and Spearman 2004)

1) Reduced WIP and cycle time: by limiting releases into the system, kanban reduced WIP and therefore results in a shorter cycle time.
2) Smoother production flow: kanban achieves a steadier, more predictable output stream by reducing fluctuations in WIP levels.
3) Improved quality: short queues reduce the time between creation and detection of a defect.

4) Reduced cost: the process of limited WIP is widely described via the analogy of lowering the water (inventory) in a river to find the rocks (problems). This results in a more efficient system with lower costs.

However, kanban is not applicable in all environments. Monden (1983) addressed that kanban is difficult, or impossible to use when there are:

1) Job orders with short production runs
2) Significant set-ups
3) Scrap loss
4) Large, unpredictable fluctuations in demand

2.3 Production scheduling in a hybrid push/pull environment

Hybrid push/pull commonly refers to the production control strategy that combines push and pull.

Spearman et al.(1990) and Spearman and Zazanis (1992) found that, while specific environment improvements are certainly important for the improved performance of pull systems (e.g., setup reduction, production smoothing), there are three primary logistical benefits:

1) There is less congestion in pull systems.
2) Pull systems are inherently easier to control than push systems.
3) The benefits of a pull environment are more related to the bounded WIP than to the practice of "pulling" everywhere.

Based on these findings, Spearman et al. (1990) proposed a hybrid push/pull system known as CONWIP, which has the benefits of a pull system but also can be applied to more general manufacturing settings. For a given production line, a limit on the work-in-process (WIP) in the line is established, and releases are not allowed into the line whenever the WIP is at or above this limit. They termed this a hybrid system because the first station in the line requires a pull signal, but the other stations in the line do not. Hence, all the operators, except the one at the first station, just process jobs when they have them, which is the same as in a push system.

Framinan et al. (2003) did a comprehensive review on the CONWIP production control system, including the operation of CONWIP, the application of CONWIP, and the comparison with other systems. In this paper, they conclude that:

1) Most of the research related to operations focuses on card setting and job sequencing; however, there are almost no papers dealing with other decisions, such as the relative importance of the different decisions in the overall performance of the system, and the impact of lot-sizing on the system performance.
2) CONWIP has proved to be applicable to a number of manufacturing scenarios, including job-shops, assembly lines, or rework, among others.
3) CONWIP has been compared to a number of production systems; however, there are no general conclusions.

Hybrid push/pull systems also have been studied by Deleersnyder et al. (1992), Hodgson and Wang (1991), Pandey and Khokhajaikiat (1996), and Wang and Xu (1997). Geraghty and Heavey (2004) give a comprehensive review about alternate hybrid push/pull strategies.

2.4 Comparison between different types of production scheduling

There are a number of papers presenting the comparison between different types of production scheduling.

Spearman et al. (1990) compare CONWIP with kanban and with push-based production control of a single production line. They conclude that the CONWIP differs from kanban in three main ways:

1) A backlog is used to dictate the part number sequence.
2) Cards are related to all parts produced on the line rather than individual part numbers.
3) Jobs are pushed between workstations in series once they are authorized by a card to start at the beginning of the line.

The differences between CONWIP and push control systems stem largely from the built-in feedback of the CONWIP system. Spearman et al. (1990) show that CONWIP can result in lower WIP levels than a kanban system with the same throughout based on theoretical reasons, which makes CONWIP better than kanban since it provides the benefits of kanban to a wider variety of situations. They also demonstrate that pull is more effective than push in many production situations for the environmental, queueing, and control effects reasons.

Bonvik et al. (1997) performed a simulation study for a short flow-line making a single part type to compare kanban, minimal blocking, basestock, CONWIP, and hybrid control. They considered constant and time-varying demand rates. The hybrid control policy demonstrated superior performance in terms of achieving a high service level with minimal inventories, closely followed by CONWIP and basestock.

Geraghty and Heavey (2004) compare the performance between hybrid push/pull in which different stages along a production line are controlled by a push or pull policy and CONWIP/pull in which kanbans are used to control WIP at individual stages as well as an overall WIP cap on inventory. They showed that the optimal hybrid push/pull is effectively CONWIP/pull.

Huang et al. (1998) developed simulation models to compare the performance among MRP, kanban and CONWIP systems implemented in a semi-continuous manufacturing environment: a cold rolling plant. The results showed that CONWIP is the most efficient among the three control systems, which can greatly decrease the WIP, average inventory and average inventory costs and meanwhile provide a higher throughput rate and facility utilization.

Karmarkar (1991) has compared the procedural distinctions between push and pull systems. He shows that the order release process and resulting information flows can be used to characterize push and pull control schemes and discusses the evolution of these control schemes. He demonstrates that various combinations or hybrid forms of these schemes are possible through the comparison of the characteristics of various types of push and pull control schemes.

Damodaran and Melouk (2002) compared push and pull systems with transportation consideration. A multiproduct, multiline, multistage production system was used to compare the two systems. It was found that the total production was drastically reduced with the introduction of transporters. In terms of throughput rate, the push system outperformed the pull system when transportation time was ignored and the opposite is true with transporter consideration. In terms of average waiting time in the system, the push system performed better than the pull system when the batch size was small; on the contrary, the pull system was better when the batch size was large.

Cheraghi and Dadashzadeh (2008) present a comparative analysis of several different production control systems in a complex factory setup via simulation. They conclude that:

1) The pull system does not outperform the push system with respect to WIP under all conditions.
2) Each of the systems performs best at a specific inter-arrival time, although it is different for each system. So no single production control system is best under all conditions.
3) The batch size shows a significant effect on the system performance of the pull system. Pull based systems prefer a smaller batch size to better control WIP.

Simulation and mathematical methodology are the most common ways to compare the performance between different strategies (Buzacott 1989; Krajewski et al. 1987; Luss 1989; Pyke and Cohen 1990; Rees et al. 1989; Spearman and Zazanis 1992). Benton and

Shin (1998) performed a comprehensive comparison of the MRP-JIT and push-pull systems, including conceptual comparison literature and analytical comparison literature.

Herer and Masin (1997) developed a mathematical programming formulation of a CONWIP-based production system in which they explained the main advantages of CONWIP over MRP systems. They demonstrated that the difference between MRP and CONWIP lies in the way inventory is handled. In MRP-ruled manufacturing systems the amount of inventory in the system is theoretically unlimited (Wight 1995). This difference causes MRP systems to have long lead time, poor service levels, and large work-in-process and finished goods (Chase et al. 1998).

Ovalle and Marquez (2003) conducted a comprehensive literature review to present the benefits of the CONWIP system in different production environments and discussed the possible utilization of CONWIP supply chain policy to manage the entire supply chain. They developed a simulation model to demonstrate the advantages of this strategy in comparison with a fully integrated supply chain, which are smaller average of orders placed; less impact of demand variability on the ordering policy; shorter average finished goods inventory, work-in-process levels, and potential inventory cost; and easier control of inventories.

CHAPTER 3 SCHEDULING AND PLANNING MODELS

3.1 MRP

A production scheduling and planning model helps decide a complete specification of the amounts and the exact timing of the production for each end item or final product. Accordingly, MRP deals with two basic functions of production control: quantities and timing. MRP must determine proper production quantities for all type of items, including final products which are sold, components which are used to compose final products and raw materials which are purchased. MRP must determine the production timing as well.

Usually the production plan is divided into three component parts:

1) The master production schedule (MPS)
2) The materials requirements planning (MRP) systems
3) The detailed job shop schedule

Each of the components is a subsystem of the entire plan.

MPS contains the demand for the MRP system, which provides the quantity and due dates for all parts that have independent demand, including all end items as well as external demand for lower-level parts. The MPS contains part numbers, need quantity, and due date for each purchase order which is used by the MRP system to obtain the gross requirements to initiate the MRP procedure. Thus MPS can be treated as input to

MRP. MPS also contains the current inventory status which is known as on-hand inventory and the status of outstanding orders (both purchased and manufacturing) known as scheduled receipts.

The basic MRP procedure is simple. We will discuss each of the steps in detail in section 3.3 where we will also discuss development of the simulation model. Here we briefly describe the MRP procedure.

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

Planned order releases, which are important outputs of a MRP system, eventually become the jobs processed in the plant which form the basis of the detailed job shop schedules.

Overall, MRP is a closed production system with two major inputs:

1) The MPS for the end item
2) The relationship between the components and subassemblies composing the end item

The method is simple and logical. However, an important assumption used in the MRP procedure is unrealistic. As mentioned previously, all the required information is assumed to be known with certainty which is not always true. There exist two key sources of uncertainty, which are the forecast demand for the future sales of the end item and the estimation of the production lead time.

Forecast uncertainty means that the actual demand is likely to be different from the demand forecast. MRP is based solely on forecast demand, so the forecast uncertainty could result in poor scheduling of recourses.

MRP assumes that the planned lead time for the production item is also known with certainty. This is used to determine the start time of the jobs by offsetting their due dates. In essence, it assumes infinite capacity. The uncertainty of the actual production lead time can result in either excess inventory or high backorder.

3.2 DRS

Detailed scheduling would be futile if the forecast which is the base of scheduling is wrong or must be re-done when conditions change (e.g. line goes down, demand changes). Instead of creating a detailed schedule for a single situation, the DRS system creates a set of policy parameters (e.g. reorder point, reorder quantity and WIP level) that work for a range of situations. The policy is dynamic which means that it depends on actual demand and actual production. The policy is risk-based which means that it considers random events and lack of knowledge (e.g. forecast inaccuracy). The optimal execution obtained from DRS policy results in a manufacturing system that is robust enough to accommodate moderate changes in demand and/or capacity without the need to reschedule, which is the dynamic control. It also can detect when the assumption regarding demand and capacity used to determine the dynamic policy is no longer valid and indicates the need for more capacity (e.g.. a makeup shift or a second shift), which is the risk-based control.

So the essential differences between MRP and DRS are:

- MRP generates detailed schedule while DRS determines optimal dynamic parameters.
- Over a planning period, the schedule must be fixed in MRP while it is dynamic in DRS.
- In MRP there is no reaction to random demand/supply (i.e. reschedule, ignore changes) while DRS automatically reacts to random demand/supply (i.e. self correcting, capacity "trigger").

3.3 Simulation models

We will now focus on the development of simulation models in order to compare the performance of the DRS strategy with the traditional MRP model for scheduling the release of orders into a manufacturing system.

3.3.1 MRP

The MRP model has three components.

In the first component, we calculate the net requirement for each product deterministically based on forecast demand and then get the planned order receipts. We then determine the planned order release by taking into consideration the production lead times (see Figure 1).

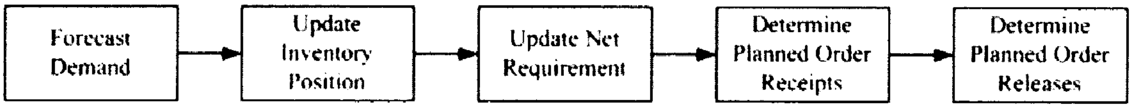

Figure 1: MRP procedure

Table 1 shows the notations used in this section.

Table 1: Notations

$D_i(t)$	forecast demand for product i in period t
$IP_i(t)$	projected inventory position for product i in period t
$D_i(0)$	demands due before the first period for product i
$w_i(t)$	on-hand inventory for product i in period t
$NR_i(t)$	net requirements for product i in period t
$PO_i(t)$	planned order receipts for product i in period t
$PW_i(t)$	planned work orders for product i in period t
h_i	holding cost rate for product i
K_i	setup cost for product i

The forecast demand for product i in period t, denoted as $D_i(t)$, $t = 0, \cdots, n$, is assumed to be known. The period in our model is one day and the planning horizon is four weeks. The projected inventory position in period t, $IP_i(t)$, is computed as:

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

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

$D_i(0)$ is the sum of the demands due before the first period. $w_i(t)$ is the current on-hand inventory.

The next step is to get the net requirement for each product in each period, $NR_i(t)$ as

$$min\{D_i(t), max\{0, -IP_i(t)\}\}$$

Then we compute the planned order receipts $PO_i(t)$. In our model we use re-order quantity Q as the lot size. Thus the planned order release is an integer multiple of Q. The last step is to assign the planned work orders. We calculate the planned lead time l by dividing re-order point by average daily demand. Then, the planned work orders, $PW_i(t)$ are given by

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

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

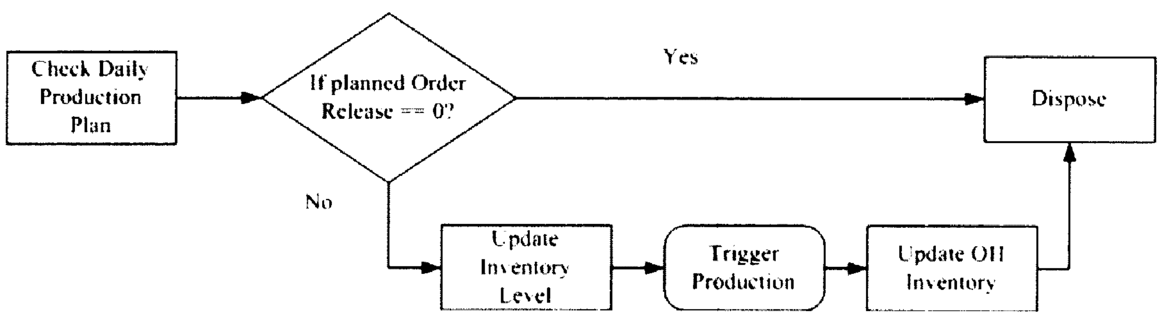

Figure 2: Production process in MRP system

The third component follows the actual order demand to update the inventory level, which is illustrated in Figure 3. When a demand is realized, we update the inventory level and compare the inventory level with the re-order point. If the inventory level is greater than re-order point, the order is filled.

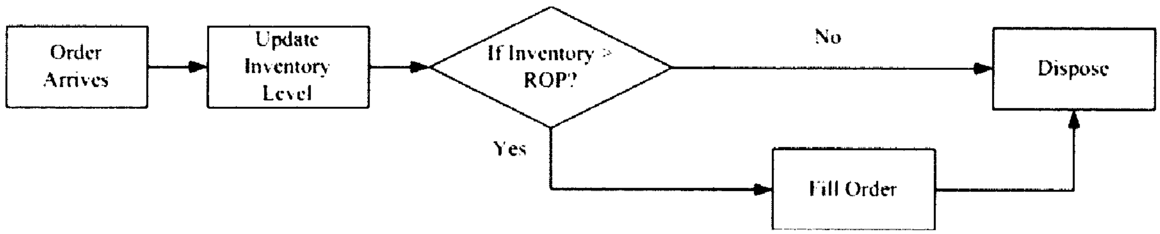

Figure 3: Order demand procedure in MRP system

For the MRP model, we also introduce the Silver-Meal heuristic which is a popular lot-sizing named for Harlan Meal and Edward Silver (1973). It can be incorporated into the MRP calculus as shown in Nahmias (2001).

To apply the Silver-Meal heuristic, we need two additional inputs: the holding cost rate h_i and the setup cost K_i. Define $C_i(T)$ as the average holding and setup cost per period if the current order spans the next T periods. As above, let $NR_i(t)$ be the net requirements over an n-period horizon. Consider period 1. If we produce just enough in period 1 to satisfy the demand in period 1, then just the order cost K_i is incurred. Therefore,

$$C_i(1) = K$$

If we produce enough in period 1 to meet the demand in both periods 1 and 2, then $NR_i(2)$ must be held for one period. Hence,

$$C_i(2) = (K + hNR_i(2))/2$$

By induction, we can get the general formula

$$C_i(j) = (K + h * NR_i(2) + 2h * NR_i(3) + \cdots + (j-1)h * NR_i(j))/j$$

Once $C_i(j) > C_i(j-1)$, stop and set the planned order receipts $PO_i(1) = NR_i(1) + NR_i(2) + \cdots + NR_i(j-1)$, and begin the same process again at period j.

Several useful constraints can be introduced into the MRP model to improve the performance, such as capacity constraint, minimal makespan constraint, and recourse policy.

In the basic MRP model, the production scheduling plan is calculated based on forecast demand without the consideration of capacity. It is clear that the introduction of capacity constraints makes a more realistic solution. However, they also make the problem more complex. Turning to the original MRP model, in addition to calculating the net requirements $NR_i(t)$ in each period, we can also assume known production capacity $C_i(t)$ in each period. Therefore, we need to find a feasible solution for planned work orders $PW_i(t)$ subject to the constraints,

$$PW_i(t) \leq C_i(t)$$

To calculate the production scheduling plan with consideration of capacity constraints, we must first obtain planned work orders $PW_i(t)$ based on the original MRP procedure. Then we compare $PW_i(t)$ with capacity $C_i(t)$. If it is greater than capacity, we need to release the excess production plan $PW_i(t) - C_i(t)$ into the following days with excess capacity, hence we get new planned work orders $PW_i(t)$, which does not violate the capacity constraints.

In addition to introducing capacity constraints to get a more realistic solution, we also consider the makespan to improve the performance, which means that the optimal order release sequence is determined based on minimizing makespan. In the MRP model, order release plan is calculated by forecast demand and planned lead time. Often, there is more than one product that can be released for production. A reasonable order release sequence could improve the system performance. Here we introduce makespan to decide the order release sequence. We calculate the makespan for each possible sequence of every product and then choose the one which minimizes the makespan. Clearly it is a reasonable way to decrease the cycle time and hence improve the system performance.

Recourse is another useful way to improve the performance. After we calculate the planned order release based on MRP procedure, we compare planned work orders $PW_i(t)$ with capacity $C_i(t)$. If the former is greater than the latter, recourse is introduced into the model, which means that a second-shift is introduced into the system. It is obviously a way to decrease the cycle time and improve the customer service.

3.3.2 DRS

In DRS model, we trigger the production based on the actual demand. When a demand occurs, the inventory level is updated. If the updated inventory level is greater than the re-order point, the order is filled. If not, we trigger a production. Then, the number of batches of production is calculated as:

$$\left\lceil \left| \frac{Available\ Inventory - ROP}{ROQ} \right| \right\rceil$$

$\lceil . \rceil$ is the smallest integer greater or equal to ".". The model is illustrated in Figure 4.

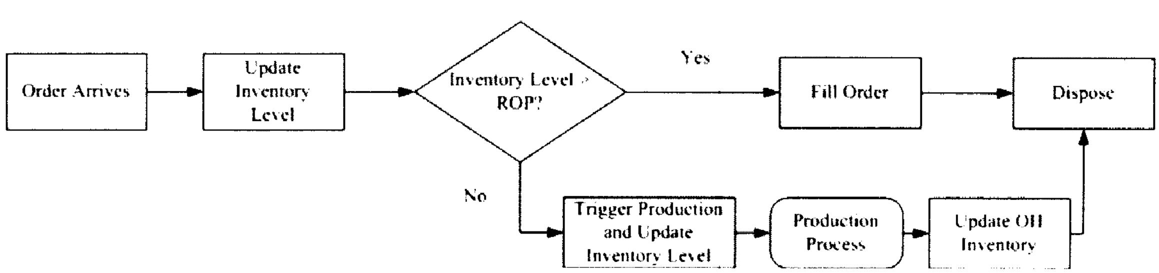

Figure 4: Production process in DRS model

For the DRS model, CONWIP and recourse constraints are also introduced to improve its performance.

CONWIP constraint is illustrated in Figure 5. Based on the DRS model discussed in the Figure 4, CONWIP constraint is introduced to control the production process. After we trigger an order production, we need to check the WIP to see if it is less than the WIP cap which is set as a constant according to the system capacity. If the current WIP is less than the WIP cap, the order can be released into the production line directly. Otherwise, the order is held outside the production line until the WIP drops below the WIP cap. In this case, by limiting order releases into the system, the CONWIP controls WIP and hence results in a lower average WIP level. This also makes cycle time shorter according to Little's Law (1961).

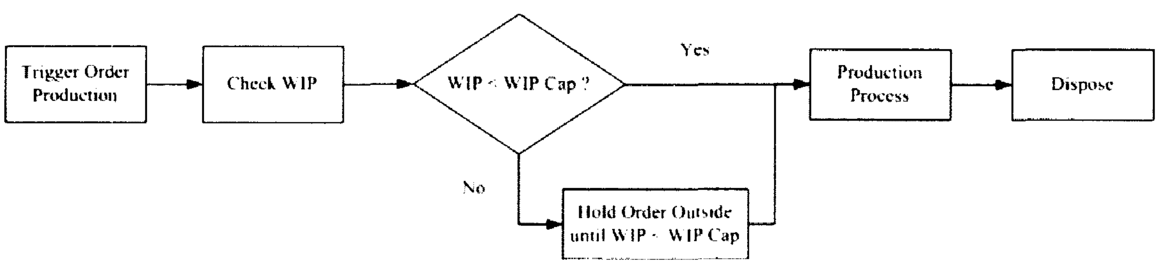

Figure 5: CONWIP constraint procedure in DRS system

Introducing CONWIP into the system also brings another benefit for monitoring the status of the system. We can watch the items waiting outside the production line which is like a virtual queue. When we apply recourse to improve the system performance, it is easy to make a decision about whether a second shift is needed based on the size of the virtual queue. We check the queue outside the production line at the end of every day (a period). If the number in the virtual queue is greater than the limit cap which is set up based on the system capacity, a second shift would be triggered. Otherwise, process line produces items in one shift.

3.4 Alternative model

In this project, we not only build the simulation for the DRS policy, but also use an analytical tool called "Lean Physics Support Tool" (LPST for short) to calculate the results for DRS model. LPST is developed by Factory Physics, Inc. This software suite consists of design, planning and execution tools based on a scientific framework that enables companies to determine how to advance their operations to the best possible levels of profitability. Figure 6 displays an input screen of the online tool. We can input necessary system parameters (e.g., number of orders per period, average order size, transfer batch, ROP, ROQ). Then we can calculate the results through this tool. An example is shown in Figure 7. We can get the system performance measurements such as cycle time, backorder, inventory, fill rate and so on. Then we can compare the results for the DRS system obtained via analytic and simulation models and demonstrate the validity of the former.

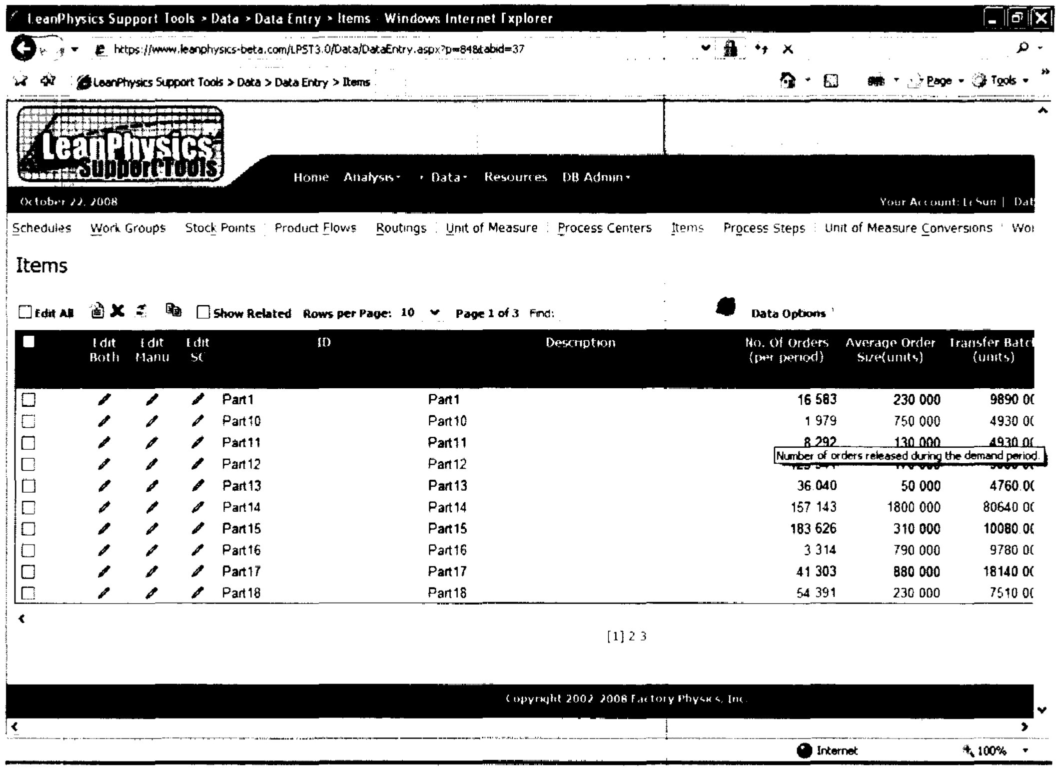

Figure 6: LPST input webpage

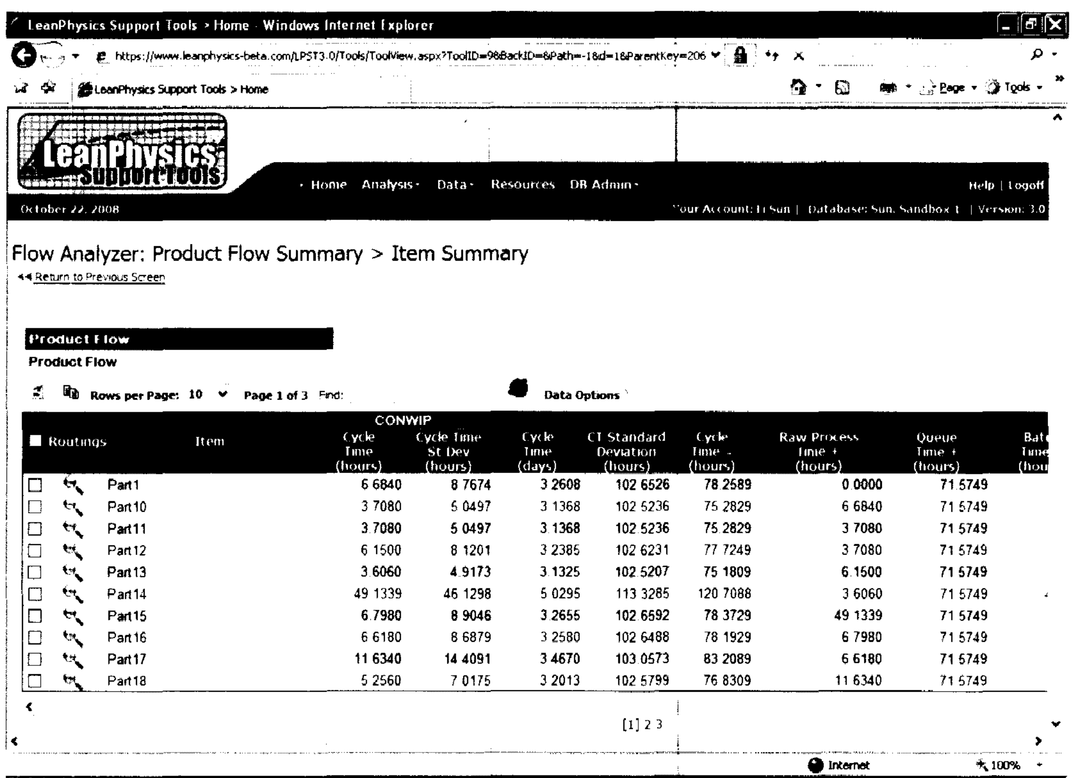

Figure 7: LPST output webpage

CHAPTER 4 NUMERICAL RESULTS

In this chapter we present the design of the experiments and show the results. We begin with a single-machine problem and then expand to multiple machines. In the single-machine problem, the system contains only one machine to produce 23 parts. In the multiple-machines problem, we have multiple work centers and each of the work centers consists of multiple machines. Multiple products need to be produced in the system as well and each product needs to go through multiple work centers. Detailed data are provided in the following sections.

4.1 Single-machine problem

To compare the MRP model with the DRS model, we used three scenarios with a single machine and 23 parts. In the first scenario, the actual order demands follow a Poisson distribution with the mean equal to the predicted order demands, which is called base scenario. The second scenario assumes that the forecast demand is over-estimated by 20% for each product which means that the actual mean demand for each product is 20% lower than the forecast demand and is called the over-estimated scenario. The third scenario assumes that the forecast demand is under-estimated by 20% for each product which means that the actual mean demand for each product is 20% higher than the forecast demand and is called the under-estimated scenario. In our model, we have 23 parts and one machine. The specific data is shown in Table 2. NrOrder refers to the average number of orders per period (one month); AvgOrdSize is the average order size for each part (assumed to be normally distributed, with the standard deviation equal to StDevOrdSize); OnHandQty is the onhand inventory; ROQ is re-order quantity, and ROP is re-order point.

For each scenario, we created two sub-scenarios. One is with moderate variability and the other is without variability. With moderate variability, the number of actual orders per period follows a Poisson distribution, the ordersize is normally distributed, and the process time is exponentially distributed, as shown in Table 2. In the no-variability scenario, all the variables, including the number of orders per period, ordersize, and process time, are constant.

Table 2: Input data for single-machine problem

Part1	**16.5826**	**16.5826**	**230**	**46**	**0**	**9890**	**519**
Part2	9.8444	9.8444	90	18	1399	9990	145
Part3	**97.45**	**97.45**	**260**	**52**	**4094**	**10370**	**2142**
Part4	203.726	203.726	500	100	37622	25920	7483
Part5	**112.5884**	**112.5884**	**260**	**52**	**4782**	**19620**	**2396**
Part6	31.9135	31.9135	370	74	1892	4930	1315
Part7	**46.2692**	**46.2692**	**130**	**26**	**2184**	**7260**	**604**
Part8	51.9272	51.9272	660	132	5087	7480	3358
Part9	**6.3083**	**6.3083**	**120**	**24**	**630**	**7510**	**145**
Part10	1.9786	1.9786	750	150	0	4930	455
Part11	**8.2923**	**8.2923**	**130**	**26**	**2023**	**4930**	**188**
Part12	125.3411	125.3411	170	34	5951	9000	1712
Part13	**36.04**	**36.04**	**50**	**10**	**1505**	**4760**	**199**
Part14	157.1427	157.1427	1800	360	70660	80640	21751
Part15	**183.6258**	**183.6258**	**310**	**62**	**11732**	**10080**	**4249**
Part16	3.3139	3.3139	790	158	4796	9780	649
Part17	**41.3034**	**41.3034**	**880**	**176**	**11336**	**18140**	**3781**
Part18	54.3913	54.3913	230	46	3446	7510	1204

Part19	14.6444	14.6444	270	54	2493	7510	560
Part20	18.6798	18.6798	1090	218	2958	7510	2681
Part21	14.0424	14.0424	1250	250	3319	9890	2538
Part22	7.7521	7.7521	230	46	3488	4930	317
Part23	8.7343	8.7343	320	64	1614	4930	479

For all the MRP and DRS models in this chapter, we run 100 replications of the simulation for 10 years with a one-year warm-up period. We use Rockwell Arena 10.0 as the simulation software on an x-86 workstation.

4.1.1 Base scenario

As mentioned previously, mean demand is equal to the forecast mean demand in the base scenario. There are two sub-scenarios under this case. One is with moderate variability, which means that the inter-arrival time of orders is exponentially distributed. The setup time and process time are also exponentially distributed. To compare the performance between MRP and DRS strategies, we mainly focus on the following measurements:

- Fill rate based on time: the fraction of time the system does not have backorders. It represents a reasonable definition of customer service.
- Fill rate based on units: represents the fraction of demand (based on units) that will be filled from stock. It represents another definition of customer service.
- Average backorder
- Average inventory

Fill rate is related to customer satisfaction, so the higher the fill rate, the greater the customer satisfaction. Backorder also is another measure of customer satisfaction, which is better when it is lower. Inventory incurs a holding cost, so a lower inventory is preferred. In an ideal situation, we need the fill rate to be as high as possible to meet customer demand, while maintaining as little inventory as possible.

Table 3-5 show the results for the DRS and MRP simulation models as well as the LPST analytical model. From the tables we can see that:

- The machine utilizations compare well among all three models, which is a basic step to demonstrate the validity of the analytical model.
- Analytical results compare well with simulation results for DRS model (i.e. comparison between LPST and Arena simulation).
- Most of the 23 parts have higher fill rates, much lower inventory and backorder in the DRS model, which can be interpreted as a system with better performance when compared to MRP model.

Table 3: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model with moderate variability

	[redacted]			[redacted]		
	DRS Simulation	**LPST 3.0**	**MRP Simulation**	**DRS Simulation**	**LPST 3.0**	**MRP Simulation**
Part 1	98.68%	98.74%	98.24%	7.54	7.72	11.03
Part 2	**99.70%**	**99.73%**	**99.56%**	**0.43**	**0.45**	**0.78**
Part 3	90.49%	92.94%	90.43%	298.26	170.75	308.89
Part 4	**83.52%**	**90.96%**	**79.58%**	**2017.46**	**580.92**	**2677.89**
Part 5	93.48%	93.88%	91.95%	233.52	199.09	309.18
Part 6	**92.10%**	**94.51%**	**88.74%**	**124.62**	**74.75**	**195.88**
Part 7	96.92%	97.06%	96.42%	23.62	23.51	30.12
Part 8	**86.21%**	**94.11%**	**83.85%**	**613.22**	**151.44**	**736.50**
Part 9	99.66%	99.69%	99.49%	0.53	0.53	0.76
Part 10	**98.73%**	**99.06%**	**97.80%**	**5.73**	**6.51**	**13.21**
Part 11	99.34%	99.39%	98.88%	1.25	1.33	2.40
Part 12	**90.48%**	**92.81%**	**88.17%**	**250.91**	**147.19**	**326.53**
Part 13	98.71%	98.76%	98.35%	3.13	3.11	4.07
Part 14	**77.82%**	**86.82%**	**74.63%**	**7657.83**	**2653.06**	**9654.70**
Part 15	81.39%	93.53%	77.39%	1286.62	188.26	1609.90

Part 16	**99.03%**	**99.17%**	**98.39%**	**5.90**	**7.08**	**11.61**
Part 17	92.51%	93.94%	90.55%	358.38	245.81	484.62
Part 18	**93.79%**	**94.65%**	**92.79%**	**100.51**	**79.89**	**123.31**
Part 19	98.28%	98.41%	97.68%	9.88	10.31	15.06
Part 20	**92.02%**	**94.81%**	**88.90%**	**231.82**	**132.27**	**356.47**
Part 21	94.46%	95.60%	91.60%	151.46	117.70	248.16
Part 22	**98.88%**	**98.98%**	**98.18%**	**3.56**	**3.82**	**6.51**
Part 23	98.32%	98.46%	97.37%	7.73	8.57	14.13

Table 4: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model with moderate variability

[redacted]	[redacted]		[redacted]	
	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.57%	97.55%	5464.40	6415.25
Part 2	**99.05%**	**99.06%**	**5172.43**	**6266.52**
Part 3	97.40%	95.37%	7332.51	8539.73
Part 4	**97.99%**	**91.00%**	**20439.79**	**21413.97**
Part 5	98.62%	95.97%	12202.94	12966.40
Part 6	**92.20%**	**88.80%**	**3777.03**	**4020.62**
Part 7	98.14%	97.40%	4237.13	4787.09
Part 8	**90.82%**	**87.75%**	**7099.59**	**8128.84**
Part 9	98.34%	98.65%	3908.73	4805.46
Part 10	**84.19%**	**87.30%**	**2916.20**	**3825.65**
Part 11	97.26%	97.60%	2643.67	3198.92
Part 12	**98.04%**	**93.97%**	**6213.09**	**6478.60**
Part 13	98.92%	98.40%	2580.09	2908.84
Part 14	**97.68%**	**90.87%**	**62070.92**	**64350.54**
Part 15	96.80%	89.26%	9285.77	10065.68
Part 16	**91.62%**	**93.81%**	**5544.75**	**7164.34**
Part 17	94.95%	92.85%	12844.14	14146.02
Part 18	**96.81%**	**95.23%**	**4953.44**	**5571.68**
Part 19	96.26%	96.39%	4311.94	5017.77
Part 20	**84.89%**	**85.07%**	**6434.03**	**7297.41**
Part 21	86.85%	86.61%	7476.37	8269.81
Part 22	**95.16%**	**95.82%**	**2779.63**	**3346.15**
Part 23	93.24%	94.28%	2943.37	3499.65

Table 5: Comparison of machine utilization estimates for DRS and MRP simulation models and LPST model

[redacted]	[redacted]
DRS Simulation	**74.57%**

LPST 3.0	74.55%
MRP Simulation	**74.58%**

Table 6 shows average results for DRS and MRP models. The difference (%) column is calculated as (DRS Simulation – MRP Simulation) / MRP Simulation, which reflects the percentage change between DRS model and MRP model. We can see that DRS simulation model obtained a higher fill rate based on time (1.68%), a lower average backorder level (21.86%), a higher fill rate based on units (1.57%) and a lower average inventory (8.92%) than MRP simulation model. Overall, DRS model has a better performance than MRP model in this single-machine problem for the base scenario with moderate variability in the system.

Table 6: Comparison between DRS and MRP simulation models for base scenario with moderate variability

Fill Rate Based on Time	**93.68%**	**92.13%**	**1.68%**
Average Backorder (units)	582.34	745.29	-21.86%
Fill Rate Based on Units	**94.91%**	**93.43%**	**1.57%**
Average Inventory (Units)	8810.09	9673.26	-8.92%

Tables 7-9 compare the performance measures for the three models assuming that the inter arrival rate, process time and set up time are constant. We can conclude that:

- Once again, the machine utilizations for the three models are very close.
- The analytical results compare well with simulation results for DRS model (i.e. comparison between LPST and Arena simulation).

- Most of the 23 parts have higher fill rates based on time, much lower backorder and inventory in DRS model, which can be interpreted as a system with better performance when compared to the MRP model.

Table 7: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model without variability

[redacted]	[redacted]			[redacted]		
	DRS Simulation	**LPST 3.0**	**MRP Simulation**	**DRS Simulation**	**LPST 3.0**	**MRP Simulation**
Part 1	100.00%	99.99%	99.00%	0.00	0.00	3.26
Part 2	**100.00%**	**100.00%**	**99.80%**	**0.00**	**0.00**	**0.24**
Part 3	99.58%	99.46%	92.92%	1.25	2.83	208.51
Part 4	**97.94%**	**98.29%**	**80.04%**	**33.69**	**34.24**	**2424.91**
Part 5	99.53%	99.52%	92.42%	1.94	2.71	266.51
Part 6	**99.97%**	**99.80%**	**92.18%**	**0.02**	**0.37**	**107.59**
Part 7	99.94%	99.90%	97.23%	0.05	0.10	18.61
Part 8	**99.85%**	**99.45%**	**87.07%**	**0.53**	**3.48**	**530.96**
Part 9	100.00%	100.00%	99.76%	0.00	0.00	0.18
Part 10	**99.63%**	**100.00%**	**99.79%**	**0.59**	**0.00**	**0.95**
Part 11	100.00%	100.00%	99.55%	0.00	0.00	0.43
Part 12	**99.51%**	**99.40%**	**89.65%**	**1.23**	**3.00**	**262.45**
Part 13	100.00%	99.98%	98.83%	0.00	0.01	2.29
Part 14	**95.71%**	**95.37%**	**75.71%**	**120.50**	**85.47**	**8415.48**
Part 15	98.57%	98.39%	78.22%	10.44	21.08	1480.85
Part 16	**99.68%**	**100.00%**	**99.32%**	**0.19**	**0.00**	**1.62**
Part 17	99.91%	99.84%	92.41%	0.40	0.69	318.66
Part 18	**99.94%**	**99.75%**	**94.23%**	**0.04**	**0.63**	**83.10**
Part 19	100.00%	99.99%	98.64%	0.00	0.00	5.58
Part 20	**99.99%**	**99.93%**	**93.63%**	**0.04**	**0.12**	**145.69**
Part 21	100.00%	99.95%	95.47%	0.00	0.05	88.87
Part 22	**100.00%**	**99.99%**	**99.24%**	**0.00**	**0.00**	**1.42**
Part 23	100.00%	100.00%	98.77%	0.00	0.00	3.82

Table 8: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model without variability

[redacted]	[redacted]		[redacted]	
	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.69%	99.48%	5499.84	5898.97
Part 2	**99.07%**	**99.15%**	**5269.02**	**5237.62**

Part 3	97.49%	98.15%	7326.29	8715.26
Part 4	**98.07%**	**91.27%**	**20458.69**	**21164.38**
Part 5	98.68%	96.91%	12201.41	12956.91
Part 6	**92.48%**	**96.16%**	**3780.82**	**4066.03**
Part 7	98.20%	98.81%	4237.03	4693.05
Part 8	**91.17%**	**94.15%**	**7177.88**	**8152.79**
Part 9	98.41%	99.21%	3917.89	4432.23
Part 10	**84.87%**	**92.82%**	**2912.68**	**3753.81**
Part 11	97.39%	99.37%	2658.18	2974.60
Part 12	**98.11%**	**96.37%**	**6216.55**	**6524.19**
Part 13	98.96%	99.31%	2580.46	2873.13
Part 14	**97.77%**	**92.43%**	**62200.53**	**64288.04**
Part 15	96.93%	91.28%	9288.11	10035.23
Part 16	**91.96%**	**96.98%**	**5518.98**	**6798.92**
Part 17	95.14%	96.05%	12854.11	14017.07
Part 18	**96.94%**	**97.39%**	**4956.72**	**5538.81**
Part 19	96.42%	98.71%	4323.03	4783.58
Part 20	**85.50%**	**95.27%**	**6434.01**	**7357.25**
Part 21	87.36%	95.02%	7473.23	8163.37
Part 22	**95.27%**	**98.11%**	**2773.71**	**3300.49**
Part 23	93.51%	97.87%	2943.70	3357.31

Table 9: Comparison of machine utilization estimates for DRS and MRP simulation models and LPST model

DRS Simulation	**74.55%**
LPST 3.0	74.55%
MRP Simulation	**74.37%**

Table 10 shows the average measures for the DRS and MRP models. Once again, we can see that DRS simulation model obtained a higher fill rate based on time, a significantly lower average backorder level, a lower fill rate based on units and a lower average inventory than the MRP simulation model. In this situation, DRS obtained a little higher fill rate based on time and even a little lower fill rate based on units, but meanwhile it got much lower inventory level, which means that it got almost the same customer satisfaction with much lower holding cost. So overall, we can say that DRS model has a better performance than MRP in this single machine case for the base scenario in the system without variability.

Table 10: Comparison between DRS and MRP simulation models for base scenario without variability

Fill Rate Based on Time	**99.55%**	**93.65%**	**6.31%**
Average Backorder (units)	7.43	624.87	-98.81%
Fill Rate Based on Units	**95.10%**	**96.53%**	**-1.48%**
Average Inventory (Units)	8826.21	9525.35	-7.34%

4.1.2 Over-estimated scenario

For the over-estimated scenario, in which case the mean demand is 20% lower than the forecast demand, we also have two sub-scenarios. One is with moderate variability in the system (i.e. exponentially distributed inter-arrival times, process time and setup time). The other is without variability in the system (i.e. constant order arrival rate, process time and setup time). Once again, we focus on fill rate, inventory and backorder for the performance comparison.

Tables 11-13 show the results for the over-estimated forecast demand scenario in the system with moderate variability. From the results, we can conclude that:

- DRS obtains similar fill rate (based on time) as MRP, with some parts having a little higher value, and some parts a little lower value. Overall there is no big difference.

- For average backorder over time, some parts have higher levels in the DRS model, and some parts have a higher level in the MRP model. We cannot make any conclusions from this result.
- MRP resulted in a little higher fill rate based on units than DRS.
- All the 23 parts obtained much lower inventory level in DRS model, which is indicative of better performance.

Table 11: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model for over-estimated scenario with moderate variability

	DRS Simulation	MRP Simulation	DRS Simulation	MRP Simulation
Part 1	99.58%	99.44%	1.67	2.52
Part 2	**99.90%**	**99.83%**	**0.09**	**0.18**
Part 3	97.06%	98.10%	58.51	36.59
Part 4	**94.05%**	**95.16%**	**448.81**	**385.69**
Part 5	97.94%	98.06%	46.95	46.40
Part 6	**97.61%**	**96.80%**	**25.60**	**38.02**
Part 7	99.05%	99.10%	5.07	5.02
Part 8	**95.43%**	**95.88%**	**130.50**	**120.50**
Part 9	99.90%	99.77%	0.09	0.29
Part 10	**99.42%**	**98.86%**	**1.91**	**5.45**
Part 11	99.82%	99.60%	0.21	0.58
Part 12	**97.01%**	**97.08%**	**49.43**	**51.02**
Part 13	99.62%	99.57%	0.63	0.79
Part 14	**89.58%**	**92.20%**	**2301.83**	**1827.44**
Part 15	93.22%	94.58%	296.75	241.30
Part 16	**99.62%**	**99.13%**	**1.58**	**5.39**
Part 17	97.66%	97.55%	73.85	80.10
Part 18	**98.19%**	**98.33%**	**18.81**	**18.23**
Part 19	99.48%	99.19%	2.32	3.94
Part 20	**97.43%**	**96.66%**	**50.80**	**74.93**
Part 21	98.23%	97.20%	34.74	58.78
Part 22	**99.62%**	**99.32%**	**0.95**	**1.78**
Part 23	99.44%	99.10%	2.10	3.42

Table 12: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model for over-estimated scenario with moderate variability

[redacted]	[redacted]		[redacted]	
	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.58%	98.56%	5469.18	6372.76
Part 2	**99.02%**	**99.36%**	**5137.42**	**6098.21**
Part 3	97.39%	98.72%	7325.53	9412.17
Part 4	**97.99%**	**98.04%**	**20443.08**	**25398.71**
Part 5	98.62%	98.78%	12214.20	13696.85
Part 6	**92.19%**	**94.51%**	**3777.51**	**4463.53**
Part 7	98.13%	98.88%	4230.16	4859.54
Part 8	**90.82%**	**95.17%**	**7097.61**	**9361.53**
Part 9	98.30%	98.87%	3927.02	4827.90
Part 10	**84.20%**	**88.93%**	**2920.56**	**3893.56**
Part 11	97.24%	98.36%	2653.94	3205.88
Part 12	**98.03%**	**98.19%**	**6211.66**	**7163.27**
Part 13	98.91%	99.30%	2581.98	2909.25
Part 14	**97.68%**	**97.98%**	**62036.18**	**75287.67**
Part 15	96.80%	97.73%	9286.69	12016.12
Part 16	**91.53%**	**94.59%**	**5536.07**	**7069.06**
Part 17	94.95%	96.98%	12848.49	15394.10
Part 18	**96.81%**	**98.21%**	**4964.83**	**5936.28**
Part 19	96.27%	97.63%	4307.49	5081.88
Part 20	**84.92%**	**91.71%**	**6434.83**	**8126.24**
Part 21	86.84%	91.34%	7483.23	8927.04
Part 22	**95.14%**	**97.01%**	**2781.15**	**3376.93**
Part 23	93.25%	96.26%	2938.97	3563.70

Table 13: Comparison of machine utilization estimates for DRS and MRP simulation models and LPST model

[redacted]	[redacted]
DRS Simulation	**59.42%**
MRP Simulation	59.75%

To summarize, we calculate the average measures for all the 23 parts in system, as shown in Table 14. DRS model obtained lower fill rate based on time, higher backorder, lower fill rate based on units and lower inventory than MRP model in this scenario (i.e. over-estimated forecast demand case with moderate variability in the system). DRS got a lower fill rate, albeit small, compared to the large decrease percentage in inventory level (i.e. 17.79%). We can conclude that in this case DRS also obtained a better performance than the MRP model.

Table 14: Comparison between DRS and MRP simulation models for over-estimated scenario with moderate variability

Fill Rate Based on Time	**97.78%**	**97.85%**	**-0.07%**
Average Backorder (units)	154.49	130.80	18.11%
Fill Rate Based on Units	**94.90%**	**96.74%**	**-1.91%**
Average Inventory (Units)	8809.03	10714.88	-17.79%

Results for the over-estimated forecast demand scenario without variability are presented in Tables 15-17. We can find that:

- For all the 23 parts, DRS obtained perfect fill rate based on time which is obviously better than the MRP model.
- Backorder level is related to fill rate based on time. Similarly, DRS obtained perfect backorder level, which is lower than that for the MRP model.
- For fill rate based on units, MRP model resulted in a little higher percentage than the DRS model.
- For all the 23 parts, DRS obtained much lower inventory level than MRP model, which is definitely a better performance.

Table 15: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model for over-estimated scenario without variability

	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	100.00%	99.88%	0.00	0.26
Part 2	**100.00%**	**99.98%**	**0.00**	**0.02**
Part 3	99.99%	99.05%	0.01	16.51
Part 4	**99.62%**	**96.97%**	**2.99**	**219.57**

Part 5	99.95%	98.96%	0.10	21.38
Part 6	**100.00%**	**98.92%**	**0.00**	**8.83**
Part 7	99.99%	99.62%	0.00	1.55
Part 8	**100.00%**	**98.16%**	**0.00**	**48.05**
Part 9	100.00%	99.95%	0.00	0.01
Part 10	**99.67%**	**99.99%**	**0.55**	**0.06**
Part 11	100.00%	99.98%	0.00	0.01
Part 12	**99.97%**	**98.25%**	**0.02**	**27.09**
Part 13	100.00%	99.83%	0.00	0.19
Part 14	**99.70%**	**94.26%**	**5.54**	**1173.56**
Part 15	99.91%	96.11%	0.38	161.79
Part 16	**99.90%**	**99.88%**	**0.04**	**0.20**
Part 17	100.00%	99.04%	0.00	24.12
Part 18	**100.00%**	**99.28%**	**0.00**	**6.43**
Part 19	100.00%	99.85%	0.00	0.45
Part 20	**100.00%**	**99.30%**	**0.00**	**10.21**
Part 21	100.00%	99.50%	0.00	6.10
Part 22	**100.00%**	**99.92%**	**0.00**	**0.09**
Part 23	100.00%	99.88%	0.00	0.17

Table 16: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model for over-estimated scenario without variability

	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.68%	100.00%	5518.21	5763.35
Part 2	**99.05%**	**99.47%**	**5174.22**	**5187.57**
Part 3	97.50%	100.00%	7322.35	9345.42
Part 4	**98.07%**	**99.87%**	**20446.93**	**25503.13**
Part 5	98.68%	100.00%	12207.63	13496.22
Part 6	**92.49%**	**99.61%**	**3782.76**	**4417.29**
Part 7	98.20%	99.83%	4240.71	4680.81
Part 8	**91.17%**	**99.51%**	**7177.03**	**9363.76**
Part 9	98.35%	99.41%	3968.77	4294.03
Part 10	**84.74%**	**93.47%**	**2917.33**	**3876.56**
Part 11	97.36%	99.73%	2662.94	2851.05
Part 12	**98.11%**	**99.76%**	**6216.58**	**7122.88**
Part 13	98.96%	99.87%	2578.83	2742.84
Part 14	**97.77%**	**99.83%**	**62206.52**	**75185.79**
Part 15	96.93%	99.87%	9285.61	12048.64
Part 16	**92.14%**	**98.49%**	**5533.85**	**6991.86**
Part 17	95.13%	99.70%	12857.69	15062.38

Part 18	**96.94%**	**100.00%**	**4956.55**	**5810.27**
Part 19	96.37%	99.83%	4317.16	4743.77
Part 20	**85.50%**	**99.52%**	**6444.46**	**7943.61**
Part 21	87.31%	99.19%	7486.73	8693.74
Part 22	**95.30%**	**98.96%**	**2786.40**	**3119.46**
Part 23	93.56%	99.25%	2942.62	3347.85

Table 17: Comparison of machine utilizations for over-estimated scenario without variability

DRS Simulation	**59.64%**
MRP Simulation	59.54%

To summarize, we calculate the average measurement for all the 23 parts to compare the overall performance between DRS model and MRP model. As shown in Table 18, we can find that DRS obtained a higher fill rate based on time, much lower backorder level, a lower fill rate based on units and a lower inventory level. Compared with the small difference in fill rate (i.e. 0.97% and -4.28%), DRS model has a big drop in inventory level (i.e. -15.96%), which also can be seen as a better performance.

Table 18: Comparison between DRS and MRP simulation models for over-estimated scenario without variability

Fill Rate Based on Time	**99.94%**	**98.98%**	**0.97%**
Average Backorder (units)	0.42	75.07	-99.44%
Fill Rate Based on Units	**95.10%**	**99.36%**	**-4.28%**
Average Inventory (Units)	8827.47	10504.01	-15.96%

4.1.3 Under-estimated scenario

For the under-estimated scenario (i.e. actual demand mean is 20% higher than forecast demand), two sub-scenarios are conducted as well. One sub-scenario is with moderate variability in the system (i.e. exponentially distributed inter-arrival time, process time and setup time). The other is without variability in the system (i.e. constant order arrival rate, process time and setup time).

A detailed comparison data is shown in Tables 19-21. We find that:

- All the 23 parts resulted in higher fill rate based on time in DRS model, which is obviously a better performance compared to MRP model.
- All the 23 parts obtained lower backorder level in DRS model, which is also a better performance compared to MRP model.
- DRS model obtained higher fill rate based on units for all 23 parts than MRP model, which is definitely a better performance.
- Some parts have higher inventory level in DRS model, and some parts have lower. No conclusion can be drawn about the inventory levels. But the parts which got higher inventory level in DRS model also had higher fill rate. For example, part 3 inventory level is higher in the DRS model but also has better fill rate.

Table 19: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model for under-estimated scenario with moderate variability

	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	94.25%	93.29%	63.14	78.64
Part 2	**98.77%**	**98.40%**	**3.28**	**4.65**
Part 3	67.22%	62.17%	2211.67	2714.65
Part 4	**55.05%**	**43.93%**	**12006.78**	**16552.43**
Part 5	75.73%	70.11%	1853.37	2481.01
Part 6	**71.01%**	**61.39%**	**943.76**	**1369.07**
Part 7	86.89%	84.36%	208.43	270.56
Part 8	**59.04%**	**49.65%**	**3784.76**	**5031.25**

Part 9	98.64%	98.26%	3.4	4.64
Part 10	**95.87%**	**94.45%**	**27.89**	**44.09**
Part 11	96.98%	96.50%	10.31	12.63
Part 12	**67.35%**	**58.11%**	**1820.04**	**2549.56**
Part 13	94.17%	93.07%	28.43	36.18
Part 14	**50.70%**	**39.04%**	**37023.29**	**50562.68**
Part 15	51.48%	37.63%	7294.04	10158.26
Part 16	**96.44%**	**95.36%**	**36.46**	**53.31**
Part 17	72.39%	65.96%	2711.76	3607.4
Part 18	**75.69%**	**71.68%**	**809.09**	**1008.46**
Part 19	92.39%	90.70%	85.09	117.18
Part 20	**70.79%**	**63.82%**	**1708.41**	**2291.73**
Part 21	78.02%	71.82%	1131.41	1579.7
Part 22	**95.09%**	**93.87%**	**27.56**	**37.03**
Part 23	92.44%	90.65%	66.08	88.55

Table 20: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model for under-estimated scenario with moderate variability

	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.59%	96.04%	5462.75	6220.93
Part 2	**99.09%**	**98.67%**	**5156.33**	**6239.01**
Part 3	97.39%	87.17%	7324.26	7194.68
Part 4	**97.99%**	**78.20%**	**20446.85**	**16524.85**
Part 5	98.63%	90.51%	12201.29	11676.33
Part 6	**92.18%**	**78.84%**	**3781.30**	**3364.84**
Part 7	98.14%	94.46%	4236.44	4520.20
Part 8	**90.82%**	**74.07%**	**7100.45**	**6460.60**
Part 9	98.35%	98.07%	3897.72	4824.03
Part 10	**84.27%**	**85.82%**	**2927.94**	**3615.75**
Part 11	97.25%	96.86%	2650.69	3132.00
Part 12	**98.04%**	**84.03%**	**6211.25**	**5348.79**
Part 13	98.91%	97.06%	2578.17	2855.99
Part 14	**97.68%**	**78.42%**	**62084.46**	**49966.60**
Part 15	96.80%	70.26%	9290.45	7170.92
Part 16	**91.58%**	**92.41%**	**5543.19**	**6862.80**
Part 17	94.96%	85.45%	12856.60	12285.70
Part 18	**96.81%**	**89.95%**	**4958.78**	**4999.76**
Part 19	96.26%	94.14%	4321.51	4772.94
Part 20	**84.92%**	**75.05%**	**6434.35**	**6209.34**

Part 21	86.87%	79.10%	7486.59	7276.87
Part 22	**95.15%**	**94.23%**	**2779.59**	**3212.94**
Part 23	93.25%	91.80%	2942.65	3327.55

Table 21: Comparison of machine utilizations for under-estimated scenario with moderate variability

DRS Simulation	**89.29%**
MRP Simulation	89.49%

To summarize, we calculate the average measures for all the 23 parts. As shown in Table 22, we can find that DRS model obtained 6.51% higher fill rate based on time, 26.62% lower backorder level, 8.57% higher fill rate based on units and 7.77% higher inventory. Notice that the actual demand is 20% higher than forecast demand in this scenario. Obviously the production plan obtained from the MRP model could not meet the actual demand, so the fill rate is lower and inventory is also lower. We could not conclude that DRS model is absolutely better than MRP model in this scenario.

Table 22: Comparison between DRS and MRP simulation models for over-estimated scenario with moderate variability

Fill Rate Based on Time	**79.84%**	**74.97%**	**6.51%**
Average Backorder (units)	3211.24	4376.25	-26.62%
Fill Rate Based on Units	**94.91%**	**87.42%**	**8.57%**
Average Inventory (Units)	8811.90	8176.67	7.77%

The last situation for the single machine case is the under-estimated scenario without variability in the system. Tables 23-25 show the detailed comparison results between DRS and MRP model. We can find that:

- All the 23 parts obtained very good fill rate based on time in DRS model, which is obviously much better than MRP model. DRS got better performance in terms of fill rate based on time.
- All the 23 parts resulted in very low backorder level in DRS model, which is much lower than MRP model. The DRS model has better performance in terms of backorder as well.
- Most of the 23 parts had much better fill rate based on units in the DRS model than in the MRP model. Only a few parts got a little worse fill rate based on units in the DRS model.
- For the inventory level, some parts had lower values in the DRS model, and some had higher values.

Table 23: Fill rate (time) and average backorder for DRS and MRP simulation models and LPST model for under-estimated scenario without variability

[redacted]	[redacted]		[redacted]	
	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	99.99%	94.03%	0.00	49.66
Part 2	**100.00%**	**98.89%**	**0.00**	**2.36**
Part 3	98.14%	63.01%	8.75	2401.86
Part 4	**94.30%**	**45.93%**	**142.20**	**14946.43**
Part 5	98.27%	71.86%	10.41	2141.40
Part 6	**99.67%**	**64.20%**	**0.46**	**1079.79**
Part 7	99.70%	86.52%	0.30	200.29
Part 8	**98.83%**	**52.29%**	**6.42**	**4334.73**
Part 9	100.00%	98.77%	0.00	1.98
Part 10	**99.30%**	**97.66%**	**1.08**	**10.94**
Part 11	100.00%	97.43%	0.00	6.89
Part 12	**98.11%**	**59.86%**	**7.88**	**2244.22**
Part 13	99.98%	93.74%	0.01	28.13
Part 14	**88.03%**	**40.04%**	**679.27**	**45926.33**
Part 15	94.65%	39.16%	60.71	9125.95
Part 16	**99.61%**	**97.10%**	**0.23**	**16.63**
Part 17	99.22%	69.27%	4.90	2815.73

Part 18	**99.30%**	**72.61%**	**1.17**	**869.90**
Part 19	99.99%	92.04%	0.01	76.71
Part 20	**99.77%**	**67.55%**	**0.39**	**1666.79**
Part 21	99.96%	76.09%	0.19	1050.33
Part 22	**99.98%**	**94.99%**	**0.00**	**21.83**
Part 23	100.00%	92.62%	0.00	49.30

Table 24: Fill rate (units) and average inventory for DRS and MRP simulation models and LPST model for under-estimated scenario without variability

[redacted]	[redacted]		[redacted]	
	DRS Simulation	**MRP Simulation**	**DRS Simulation**	**MRP Simulation**
Part 1	97.65%	97.97%	5510.99	6106.17
Part 2	**99.15%**	**99.10%**	**5151.24**	**5548.06**
Part 3	97.50%	88.44%	7325.05	7185.35
Part 4	**98.07%**	**81.53%**	**20451.38**	**16706.36**
Part 5	98.67%	91.93%	12198.97	11732.72
Part 6	**92.49%**	**85.72%**	**3782.14**	**3445.47**
Part 7	98.20%	96.72%	4233.78	4502.37
Part 8	**91.17%**	**81.32%**	**7177.44**	**6620.60**
Part 9	98.46%	98.94%	3859.20	4460.48
Part 10	**84.91%**	**93.05%**	**2902.66**	**3542.33**
Part 11	97.32%	98.49%	2660.51	2941.46
Part 12	**98.11%**	**85.79%**	**6216.36**	**5373.98**
Part 13	98.96%	97.84%	2583.01	2872.92
Part 14	**97.76%**	**80.22%**	**62196.31**	**49516.72**
Part 15	96.93%	73.55%	9286.34	7332.15
Part 16	**92.03%**	**96.18%**	**5508.15**	**6562.29**
Part 17	95.16%	91.35%	12848.96	12537.96
Part 18	**96.94%**	**91.35%**	**4956.03**	**4932.23**
Part 19	96.40%	96.16%	4309.62	4714.17
Part 20	**85.50%**	**85.61%**	**6439.57**	**6339.13**
Part 21	87.34%	88.73%	7475.01	7365.83
Part 22	**95.34%**	**96.26%**	**2778.76**	**3059.59**
Part 23	93.48%	95.64%	2948.24	3242.55

Table 25: Comparison of machine utilizations for under-estimated scenario without variability

[redacted]	[redacted]
DRS Simulation	**89.45%**

MRP Simulation	89.14%

To summarize, we calculate the average measures for all the 23 parts. From Table 26 we can find that DRS resulted in 28.38% higher fill rate based on time, 98.96% lower backorder, 4.57% higher fill rate based on units and 8.66% higher inventory. In this situation (i.e. under-estimated forecast demand scenario without variability in system), DRS improves the customer service performance significantly (i.e. 28% increase in fill rate based on time and 4.57% increase in fill rate based on units) associated with a slight increase in inventory (i.e. 8.66%).

Table 26: Comparison between DRS and MRP simulation models for under-estimated scenario without variability

Fill Rate Based on Time	**98.56%**	**76.77%**	**28.38%**
Average Backorder (units)	40.19	3872.53	-98.96%
Fill Rate Based on Units	**95.11%**	**90.95%**	**4.57%**
Average Inventory (Units)	8817.38	8114.82	8.66%

4.1.4 Conclusions

In order to summarize the comparison results between DRS model and MRP model, we compare the overall average performance measurements (i.e. fill rate based on time, backorder, fill rate based on units and inventory) for the above six scenarios and group them relative to variability in the inter-arrival, process and setup times. Table 27 shows the comparison results summary for the system with moderate variability, including base scenario, over-estimated and under-estimated forecast demand scenarios. Table 28 shows the comparison results summary for the system without variability.

Table 27: Comparison summary between DRS and MRP simulation models with moderate variability

Base scenario	**93.68%**	**92.13%**	**582.34**	**745.29**	**94.91%**	**93.43%**	**8810.09**	**9673.26**
over-estimated	97.78%	97.85%	154.49	130.80	94.90%	96.74%	8809.03	10714.88
under-estimated	**79.84%**	**74.97%**	**3211.24**	**4376.25**	**94.91%**	**87.42%**	**8811.90**	**8176.67**

Table 28: Comparison summary between DRS and MRP simulation models without variability

Base scenario	**99.55%**	**93.65%**	**7.43**	**624.87**	**95.10%**	**96.53%**	**8826.21**	**9525.35**
over-estimated	99.94%	98.98%	0.42	75.07	95.10%	99.36%	8827.47	10504.01
under-estimated	**98.56%**	**76.77%**	**40.19**	**3872.53**	**95.11%**	**90.95%**	**8817.38**	**8114.82**

In the system with moderate variability, we can conclude that:

- For the base scenario, DRS obtained higher fill rate, lower backorder and lower inventory, which is absolutely better performance than MRP model.
- For the over-estimated forecast scenario, DRS obtained slightly reduced fill rate than MRP model, and meanwhile had much lower inventory.
- For the under-estimated forecast demand scenario, DRS obtained higher fill rate and higher inventory than the MRP model.

In the system without variability, we can find that:

- For the base scenario, DRS resulted in higher fill rate based on time, much lower backorder, slightly lower fill rate based on units and much lower inventory, which is better performance compared to MRP model.

- For the over-estimated scenario, DRS obtained higher fill rate based on time, much lower backorder, lower fill rate based on units and much lower inventory, which should be a better performance compared to MRP model.
- For the under-estimated scenario, DRS got a much higher fill rate based on time, much lower backorder, higher fill rate based on units and slightly higher inventory. Improvement of fill rate in DRS model is much higher than the increase in inventory. Therefore the DRS model has better performance than MRP.
- Comparing the results for DRS model among the three scenarios (i.e. base scenario and over-estimated and under-estimated forecast demand), we find that the performance measurements are similar, which means that DRS model is very robust even with a forecast bias.
- Comparing the results for MRP model among the three scenarios, we find that the performance measurements change a lot according to the forecast bias. Over-estimated forecast demand causes a big increase in inventory. And under-estimated forecast demand results in a large reduce in fill rate. Therefore we can conclude that MRP model is not robust for the forecast bias.

4.2 Multiple-machine problem

We extend to multiple machines cases. We set up several examples. First we develop a basic multiple-machine example to compare with other analytical results in order to demonstrate the validity of the models. Then we build the MRP and DRS models with different product types and workstation information. We also introduce several constraints into the models to improve the performance, such as makespan, capacity and recourse constraints into MRP and CONWIP and recourse constraints into DRS model. As in the single-machine case, we also build MRP-based and DRS models for three demand scenarios (i.e. base scenario, over-estimated and under-estimated scenarios).

4.2.1 Comparison between simulation models and analytical models

Simulation is frequently used to validate the results obtained from analytical models. Since analytical models are usually more flexible and efficient than simulation models, they are beneficial alternatives. But analytical models are extremely complex because of stochastic operating environment for many problems. Hence validation of analytical models is important. We compare the simulation models with three analytical models in order to demonstrate the validity and usefulness of analytical models. The first is LPST, which was already referred to in section 3.4. The second analytical model is Manufacturing system Performance Analyzer (MPA). MPA is an open queuing network model of manufacturing system that is based on Whitt's (1983) Queuing Network Analyzer (QNA) and refined, adapted and extended it in several ways. It is developed by Meng and Heragu (2004). The third analytical tool is Rapid Analysis of Queuing Systems (RAQS), which is a software package for analyzing general queuing network models based on a two-moment framework, which is a Windows application developed at Oklahoma State's Center for Computer Integrated Manufacturing Enterprises (Kamath et al. 1995).

In this section, we develop two multiple-machine examples. In both examples, the system includes multiple workstations and multiple products. In the first example, not all the products need to be processed through every workstation. In the second example, all the products go through all the workstations.

In the first example, there are four workstations. Workstation 1 contains only one machine. Workstations 2 and 4 contain two machines each. Workstation 3 contains six machines. Three products need to be processed in this system. The order inter-arrival time for each product is exponentially distributed. Table 29 shows the order information for each product. One period has 8 hours and the time unit is hour in Table 29. The process batch size is equal to the order size, which is constant in this case.

Table 29: Products Input

Mean Period Demand	1.8	2	0.3333
Mean time between dmd	17.7778	4	72.0072
Std Dev time between dmd	17.7778	4	72.0072
Process Batch Size	4	1	3

In this system, the setup time and process time of each product in each workstation is exponentially distributed. Detailed data are shown in Tables 30 and 31. If the process time equals 0 in a workstation, it means that the product does not go through that workstation. For example, we can tell from Table 31 that product 3 is processed only in workstation 3 and the mean process time is 10 hours.

Table 30: Setup Time (hours) Input

PN1	4	10	0	0
PN2	0	0	0	0
PN3	0	0	0	0

Table 31: Process Time (hours) Input

PN1	2	5	10	2
PN2	0	0	10	2
PN3	0	0	10	0

Then we can develop the simulation models and analytical models to compare the results in order to demonstrate the validity of the models. Table 32 compares the machine utilization obtained via the simulation model and three analytical models. Table 33 compares the cycle time (CT) and its standard deviation (CT STD). We find that the results compare very well, which is a sufficient validity of models.

Table 32: Comparison of Machine Utilization

[redacted]				
PC 1	67.51%	67.50%	67.50%	67.50%
PC 2	84.42%	84.38%	84.40%	84.38%
PC 3	86.08%	86.11%	86.10%	86.11%
PC 4	47.51%	47.50%	47.50%	47.50%

Table 33: Comparison of Cycle Time

[redacted]						
	CT	CT STD	CT	CT	CT STD	CT	CT STD
Part 1	208.12	113.59	209.82	209.08	109.45	208.87	115.98
Part 2	31.93	29.88	32.76	31.88	24.49	31.75	29.62
Part 3	48.36	40.75	49.22	48.48	37.29	48.50	40.78

We extend the multiple-machine case to a more complex situation, in which there are 4 workstations and 3 products. Each product must be processed at every workstation. Similarly, Table 34 shows the product order information. The order inter-arrival time is also exponentially distributed.

Table 34: Product Input

[redacted]

Mean Period Demand	**0.9**	**1**	**0.3333**
Mean Time between Demand	35.55556	48	72.0072
Std Dev Time between Demand	**35.55556**	**48**	**72.0072**
Process Batch Size	4	6	3

Tables 35 and 36 show the setup time and process time, which are also exponentially distributed.

Table 35: Setup Time Input

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
PN1	**4**	**10**	**20**	**20**
PN2	4	10	20	15
PN3	**4**	**6**	**20**	**20**

Table 36: Process Time Input

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
PN1	**2**	**5**	**2**	**2**
PN2	2	5	5	2
PN3	**2**	**1**	**10**	**4**

The machine utilization, cycle time and the standard deviation of cycle time are compared for the simulation and analytical models in Tables 37 and 38. We find that the results compare well once again demonstrating validity of the analytical models.

Table 37: Comparison of Utilization

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
PC 1	**80.98%**	**80.97%**	**80.90%**	**80.97%**
PC 2	90.13%	90.10%	90.00%	90.11%
PC 3	**42.05%**	**42.06%**	**42.00%**	**42.06%**
PC 4	89.72%	89.72%	89.70%	89.73%

Table 38: Comparison of Cycle Time

[redacted]	[redacted]		[redacted]	[redacted]		[redacted]	
	CT	**CT STD**	**CT**	**CT**	**CT STD**	**CT**	**CT STD**

Part 1	430.04	233.88	429.15	426.87	229.92	415.95	232.87
Part 2	**458.95**	**238.32**	**464.15**	**461.84**	**235.24**	**450.94**	**238.12**
Part 3	439.41	239.50	432.15	429.76	232.28	418.94	235.21

4.2.2 Comparison between MRP-based and DRS systems

In this system, also we have four workstations and three products. The first workstation has four machines and the others all have three machines each. Table 39 shows the product information. Here one period is one day (i.e. 24 hours) and time unit is hours. We can see that order inter arrival time is exponentially distributed. The order size is constant. All the three parts need to be processed by all the four workstations. Tables 40 and 41 show the setup time and process time for each product in each workstation. All the times are exponentially distributed.

Table 39: Product Information

[redacted]	[redacted]	[redacted]	[redacted]
Mean Period Demand	**0.666667**	**1**	**0.545455**
Mean time between dmd	9	8	11
Std Dev time between dmd	**9**	**8**	**11**
Order Size	6	8	6

Table 40: Setup Time Information

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
PN1	**5**	**6**	**3**	**4**
PN2	6	5	4	5
PN3	**4**	**6**	**4**	**6**

Table 41: Process Time Information

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
PN1	**1.5**	**1**	**0.5**	**1**
PN2	1	1	1	0.5
PN3	**1**	**1**	**1**	**1.5**

We develop the MRP-based and DRS models to compare the performance of the two systems. As before there are three scenarios in each system (base scenario, over-estimated and under-estimated scenarios).

4.2.2.1 DRS

4.2.2.1.1 DRS

We build basic DRS model under three scenarios (i.e. base scenario, over-estimated and under-estimated scenarios). The parameters (i.e. reorder point and reorder quantity) are as shown in Table 42.

Table 42: ROP and ROQ for three parts

Part1	190	24
Part2	310	32
Part3	190	24

In Tables 43 and 44, we show the results for the base scenario, in which the actual order inter arrival time follows exponential distribution. The performance measures in Table 43 are explained below.

- Inventory position: Represents the balance of on-hand inventory, backorder, and replenishment orders (i.e. inventory position = on-hand inventory –backorders + orders).
- OH Inventory: Stands for on-hand inventory, which represents physical inventory in stock, hence can never be negative.
- Backorder: The average number of orders waiting to be filled.

- Cycle time: The average time from when a job is released into the system until it reaches an inventory point at the end of the routing.
- STD CT: Stands for standard deviation of cycle time.
- Fill rate time: The fill rate (based on time) and represents the customer service level.

Table 43: Results of DRS model in base scenario

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Part1	200.97	66.98	5.19	200.72	82.86	87.28%
Part2	323.99	107.82	6.73	215.98	86.44	89.07%
Part3	200.97	85.37	1.89	212.04	85.04	93.90%

Table 44: Utilization of DRS model in base scenario

[redacted]	[redacted]
WC1	74.15%
WC2	89.04%
WC3	72.80%
WC4	79.63%

We find that the bottleneck resource (Workcenter 2) in this case is utilized 89.04%. Because the utilization is so high, we find that if the forecast error increases, the bottleneck resource utilization also increases significantly and the production line buildup begins to increase more. This occurs even if we only increase the forecast error by 10%.

Tables 45 and 46 show the performance of the DRS and MRP models for the 10% under-estimated forecast scenario, where the mean actual demand is 10% more than forecast demand. We find that:

- Inventory Position does not change significantly when compared to the base scenario.
- On-hand inventory and fill rate decrease significantly, as expected.
- Backorder and cycle time also increase dramatically.
- Bottleneck resource utilization increases to 97.38%, which is rather high. We can reasonably conjecture that high bottleneck utilization causes a long waiting line in the system, making the cycle times long, backorder high and fill rate low.

Table 45: Results of DRS model in under-estimated scenario

Part1	201.01	-83.67	102.35	389.23	194.05	33.40%
Part2	324.01	-117.31	147.63	402.11	194.84	35.17%
Part3	201.00	-38.14	66.37	400.46	194.96	45.67%

Table 46: Utilization of DRS model in under-estimated scenario

WC1	81.56%
WC2	97.38%
WC3	79.45%
WC4	86.83%

The results of over-estimated forecast scenario, in which the actual demand is 10% lower than forecast demand, are shown in Tables 47 and 48. We find that:

- Inventory position is almost at the same level as in the base scenario
- Cycle time decreases compared to the base scenario, resulting in higher on-hand inventory, lower backorder and higher fill rate
- Bottleneck resource utilization decreases to 80.09%, which is more acceptable than in the base scenario

Table 47: Results of DRS model in over-estimated scenario

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
Part1	201.01	106.84	0.22	156.84	63.52	98.79%
Part2	323.98	168.93	0.25	172.52	67.95	99.20%
Part3	200.98	117.74	0.05	169.62	66.26	99.66%

Table 48: Utilization of DRS model in over-estimated scenario

[redacted]	[redacted]
WC1	66.75%
WC2	80.09%
WC3	65.55%
WC4	71.43%

4.2.2.1.2 DRS with CONWIP constraint

We add a CONWIP constraint to the basic DRS model where we use the average WIP level from the base scenario as a cap on the inventory.

Table 49 shows the results for the base scenario with the CONWIP constraint. Here we have two parameters for cycle time. In this table, cycle time is the same as what we had in the basic model, and it represents the time between when a job is released until it reaches the end point of the production line. The column labeled as "CT O" represents the cycle time plus the time the job waits outside the production line in the virtual queue when the current WIP level is greater than the WIP cap. From the results, we can see that the cycle time is reduced. However the cycle time plus the waiting time in the virtual queue increases, which explains the lower on-hand inventory level, higher backorder lever, and hence the lower fill rate compared to the basic DRS model in the base scenario.

Table 49: Results of DRS model with CONWIP constraint added to the base scenario

[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]

Part1	200.99	19.68	35.43	185.59	63.47	272.05	71.40%
Part2	324.00	95.34	7.18	199.97	67.62	228.95	87.38%
Part3	201.00	45.94	21.28	198.05	66.93	283.85	78.35%

Table 50 shows the results for the under-estimated scenario (i.e. actual demand is 10% greater than the forecast demand). We find that cycle time plus the waiting time outside the production line increases dramatically which explains why the backorder level increases and fill rate decreases significantly. This is much worse when compared to basic DRS model. From the difference between cycle time and "CT O", we can conclude that the production batches have a dramatic waiting time outside the production line in the virtual queue which results in a deterioration of the overall performance. The long external waiting times result from the CONWIP constraints, where we use the same WIP cap as in the basic scenario while the larger actual demand increases the number of production batches waiting outside the production line. We can conclude that the CONWIP cap must be chosen carefully. An inappropriate number can worsen the performance.

Table 50: Results of DRS model with CONWIP in under-estimated scenario

Part1	200.99	-8568.87	8568.88	201.42	61.76	11965.78	0.05%
Part2	323.98	-74.63	100.44	214.42	66.40	362.19	37.23%
Part3	200.98	-7081.61	7081.72	215.35	65.58	12105.94	0.22%

We add the CONWIP constraint in the basic DRS model for the over-estimated scenario (i.e. actual demand is 10% lower than forecast demand). The result is shown in Table 51. We find that the results are similar to the basic model, which can be explained by the closeness of the cycle time and "CT O" values.

Table 51: Results of DRS model with CONWIP in over-estimated scenario

Part1	201.03	104.13	0.76	156.28	61.92	161.57	97.87%
Part2	324.04	166.79	0.33	171.47	66.25	174.52	99.05%
Part3	201.03	115.75	0.33	168.76	65.31	174.42	99.00%

4.2.2.1.3 DRS with recourse constraint

From the results of CONWIP constraint in the previous section, we find that CONWIP by itself is not effective in improving the performance. However, when it is used along with a recourse constraint, which means that additional capacity, for example a second shift, is added to the production line dynamically whenever there is an excessive number of jobs waiting outside the network. Because CONWIP cap represents a reasonable capacity of the production line, monitoring the number of waiting items outside the production line in the virtual queue could be an acceptable way to decide whether or not a second shift is needed. In our model, we set up a cap for the waiting items outside the production line, which could be a signal to trigger the second shift. When the number of the waiting items outside the production line is greater than the cap, a second shift is triggered.

Tables 52-54 show the results for the base scenario, under-estimated scenario and over-estimated scenario for the recourse constraint model. We find that for the base scenario and over-estimated scenario, the recourse constraint does not result in an obvious improvement when compared to the basic DRS model. This can be interpreted as follows. Even without the second shift, the basic DRS model already had a good performance. This means that the original capacity was already able to meet the demand and recourse is not necessary. In the under-estimated scenario, the backorder decreases and fill rate increases dramatically compared to the basic model. So we can conclude that recourse based on CONWIP constraint is an effective way to check when the production line capacity cannot meet the production requirements.

Table 52: Results of DRS model with recourse in base scenario

Part1	201.01	64.51	4.03	179.82	62.25	205.26	87.22%
Part2	323.99	113.43	1.88	194.58	66.90	209.96	93.71%
Part3	201.00	81.37	1.51	192.71	65.83	219.62	94.05%

Table 53: Results of DRS model with recourse in under-estimated scenario

Part1	200.99	13.05	17.28	185.17	61.46	256.19	58.94%
Part2	323.98	62.98	7.29	197.38	66.07	236.47	81.00%
Part3	201.01	34.75	9.37	198.19	65.44	277.83	72.91%

Table 54: Results of DRS model with recourse in over-estimated scenario

Part1	201.00	105.84	0.22	155.10	61.16	158.38	98.82%
Part2	324.03	168.01	0.23	171.05	66.51	173.55	99.16%
Part3	201.02	116.46	0.11	167.87	64.96	171.85	99.37%

4.2.2.2 MRP

We now consider the MRP model and test the effect of updating frequency on the MRP model. We consider three different updating frequencies (i.e. update once each week, every two weeks, and every four weeks). We also introduce makespan, capacity, and recourse constraints into the MRP model.

4.2.2.2.1 MRP with one-week update period

Tables 55-57 show the results for MRP with one-week updating frequency, including base, under-estimated and over-estimated scenarios. We compare the three scenarios and conclude that forecast error affects the performance of the MRP models. When the actual demand is higher than the forecast demand (i.e. under-estimated scenario), the cycle time and backorder increase dramatically, hence fill rate decreases dramatically. When the actual demand is lower than the forecast demand, the cycle time and backorder decrease, inventory increases, and hence fill rate improves.

Table 55: Results of MRP model with one-week update in base scenario

Part1	204.66	66.56	5.94	206.81	85.29	86.05%
Part2	325.21	102.95	8.31	222.51	89.10	87.22%
Part3	209.60	90.12	2.22	219.50	88.81	93.77%

Table 56: Results of MRP model with one-week update in under-estimated scenario

Part1	198.35	-128.91	141.74	445.16	211.08	23.32%
Part2	315.56	-191.13	210.87	460.19	212.94	24.15%
Part3	204.40	-69.85	92.66	457.29	211.36	36.17%

Table 57: Results of MRP model with one-week update in over-estimated scenario

Part1	212.43	117.59	0.23	158.44	64.48	98.84%
Part2	336.97	180.18	0.31	175.01	69.34	99.04%
Part3	215.29	131.18	0.08	170.84	67.75	99.62%

4.2.2.2.2 MRP with two-week update period

Tables 58-60 show the results for MRP with two-week updating frequency, including base, under-estimated and over-estimated scenarios. The effect of forecast error is similar as in the one-week update model. We can find that:

- In the two-week update model, the inventory position and on-hand inventory is lower than in the one-week update model in the base scenario. However, the fill rate is also lower than in the one-week update model. So it is hard to conclude which one is better.
- In the under-estimated scenario, the inventory is lower in the two-week update model than in the one-week scenario which indicates better performance. However the fill rate is also lower.
- In the over-estimated scenario, the inventory is higher than in the one-week update model and the fill rate is similar. We can say that in the over-estimated scenario, one-week update model is better than the two-week update model.

Table 58: Results of MRP model with two-week update in base scenario

Part1	200.76	65.08	6.74	203.72	83.03	84.36%
Part2	319.64	100.89	8.64	218.54	86.16	85.80%
Part3	206.46	89.67	2.11	214.24	84.54	93.27%

Table 59: Results of MRP model with two-week update in under-estimated scenario

Part1	186.49	-169.84	180.01	485.49	221.61	18.70%
Part2	298.32	-253.57	268.58	500.53	222.59	18.94%
Part3	195.19	-102.74	120.74	496.58	222.66	29.67%

Table 60: Results of MRP model with two-week update in over-estimated scenario

Part1	215.29	120.37	0.38	158.20	65.16	98.51%
Part2	342.48	185.19	0.33	174.64	69.84	99.05%
Part3	218.84	135.55	0.08	170.21	67.80	99.53%

4.2.2.2.3 MRP with four-week update period

Tables 61-63 show the results for MRP with four-week updating frequency, including the base, under-estimated and over-estimated scenarios. The effect of forecast error is similar as in the one-week update model. A comparison between the four-week update model and the two-week update model yields similar observation as in the comparison between the two-week update and the one-week update model.

Table 61: Results of MRP model with four-week update in base scenario

Part1	197.80	63.17	8.57	202.05	83.82	81.54%
Part2	315.16	97.57	12.07	217.48	86.69	82.69%
Part3	204.45	88.27	3.10	213.56	85.59	91.45%

Table 62: Results of MRP model with four-week update in under-estimated scenario

Part1	167.75	-163.29	172.55	451.63	226.38	17.76%
Part2	269.01	-243.39	256.89	466.32	227.24	17.54%
Part3	179.17	-97.62	114.47	461.45	227.15	29.48%

Table 63: Results of MRP model with four-week update in over-estimated scenario

Part1	225.16	129.66	0.39	159.18	64.31	98.46%
Part2	357.36	200.17	0.25	175.04	68.42	99.05%
Part3	224.64	140.50	0.14	170.68	67.09	99.31%

4.2.2.2.4 MRP with Silver-Meal heuristic algorithm

Now we introduce the Silver-Meal heuristic algorithm into the MRP model as a way of developing advanced planning optimization (APO) models, such as those used in industry. We assume the holding cost to be $1 per unit per day and the total set up time of a part type as the order cost for each part type. Table 64 shows the results for the base scenario. One more performance measure, namely the total number of orders in the simulation run, is included in Table 64. We calculate the average total cost (holding cost + order cost) for the base MRP model and Silver-Meal augmented MRP model. The Silver-Meal MRP obtains a lower total cost, but at the expense of the fill rate when compared to the basic MRP model.

Table 64: Results of MRP model with Silver_Meal algorithm in base scenario

Part1	200.33	27.91	18.73	244.37	112.72	67.72%	4095.30
Part2	312.73	71.18	20.33	214.93	106.33	75.34%	7349.00
Part3	203.31	66.61	6.31	234.84	107.21	85.64%	4117.90

4.2.2.2.5 MRP with makespan constraint

When we release jobs into the production line, we follow the FIFO (first-in-first-out) rule in the basic MRP. In this subsection, we introduce the makespan constraint into the basic MRP model, which means that we determine the sequence in which to release jobs so as to minimize makespan. Part 3 has the highest priority to be released, part 2 is the second one and part 1 has the lowest priority. Table 65 shows the results for the MRP model with makespan constraint under the base scenario.

- Part 1 has a higher cycle time compared to the basic MRP model. This part has a higher backorder and lower fill rate, due to the low priority assigned to part 1.
- Parts 2 and 3 have lower cycle time compared to the basic MRP model. These parts have lower backorder and higher fill rate, because parts 2 and 3 have a higher priority.

Table 65: Results of MRP model with Makespan constraint in base scenario

Part1	**205.03**	**63.25**	**7.05**	**213.76**	**90.82**	**84.12%**
Part2	324.71	107.34	7.18	216.94	86.68	88.15%
Part3	**209.47**	**94.80**	**1.63**	**210.10**	**84.78**	**95.31%**

4.2.2.2.6 MRP with capacity constraint

In the basic MRP model, capacity constraints are not considered. The implicit assumption is that the production line has infinite capacity. Because this assumption is not reasonable, we introduce capacity constraints into the basic MRP model, which is what we did with the CONWIP constraint in the DRS model. According to the WIP cap in the CONWIP DRS model, we set up an upper bound on capacity for each part type in the MRP model, which is calculated based on some specific proportion of CONWIP cap. For example, part 1 capacity is calculated by:

$$\frac{\lambda_1}{\lambda_1+\lambda_2+\lambda_3} \times WIP\ Cap$$

λ_1, λ_2 and λ_3 represent the arrival rates of parts 1, 2 and 3.

We add the MRP capacity constraint to the basic MRP model, considering all three scenarios (base, under-estimated and over-estimated scenarios) with three different updating frequencies.

Tables 66-68 show the results for the three scenarios with the one-week update model. The comparison among the three scenarios is similar as in the basic MRP model.

- In the base scenario, the capacity constraint results in a little shorter cycle time, hence a little higher inventory level, lower back order and a little higher fill rate compared with the basic model, which shows that the chosen capacity upper bound is effective.
- In the under-estimated scenario, capacity constraint results in a much higher cycle time, hence much lower inventory, and higher backorder than the basic model.
- In the over-estimated scenario, there is no obvious difference between the model with capacity constraint and the basic model. The capacity constraint does not have much of an effect.

Table 66: Results of MRP model with capacity constraint and one-week update in base scenario

Part1	204.86	67.95	5.52	205.59	84.75	86.84%
Part2	325.64	104.85	8.19	221.01	88.19	87.56%
Part3	209.60	90.36	2.06	218.11	87.07	94.29%

Table 67: Results of MRP model with capacity constraint in under-estimated scenario

Part1	198.60	-150.44	163.76	476.04	254.21	24.32%
Part2	315.34	-225.77	245.94	491.13	254.63	24.07%
Part3	204.32	-87.68	110.31	486.46	254.17	35.87%

Table 68: Results of MRP model with capacity constraint in over-estimated scenario

Part1	212.08	116.71	0.33	158.75	65.21	98.72%
Part2	336.26	179.66	0.28	173.88	68.53	99.09%
Part3	215.45	131.73	0.05	170.50	67.61	99.67%

Tables 69-71 show the results for three scenarios in the two-week update model. The comparison among the three scenarios is similar as in the basic MRP model. The comparison between the basic model and the capacity constrained model is similar to that in the one-week update model comparison.

Table 69: Results of MRP model with capacity constraint and two-week update in base scenario

Part1	200.72	66.88	5.89	200.32	80.99	85.14%
Part2	321.40	106.72	7.24	215.67	84.72	87.25%
Part3	206.69	91.30	1.90	211.68	82.86	93.67%

Table 70: Results of MRP model with capacity constraint and two-week update in under-estimated scenario

Part1	169.51	-148.52	156.97	434.52	185.45	15.36%
Part2	271.19	-224.11	236.12	449.61	186.52	15.56%
Part3	181.41	-86.26	102.29	445.94	186.33	26.59%

Table 71: Results of MRP model with capacity constraint and two-week update in over-estimated scenario

Part1	214.35	118.65	0.33	158.69	64.20	98.29%
Part2	342.46	185.90	0.25	174.21	68.15	99.11%
Part3	218.36	134.52	0.05	170.68	67.28	99.69%

Tables 72-74 show the results for all the three scenarios for the four-week update model. The comparison among the three scenarios is similar as in the basic MRP model. The comparison between the basic model and the capacity constrained model is similar to that in the one-week update model comparison.

Table 72: Results of MRP model with capacity constraint and four-week update in base scenario

Part1	199.09	66.25	7.71	199.83	82.70	83.39%
Part2	314.71	98.43	11.17	215.82	87.08	83.47%
Part3	205.12	90.23	2.99	211.42	85.07	91.59%

Table 73: Results of MRP model with capacity constraint and four-week update in under-estimated scenario

Part1	169.51	-148.52	156.97	434.52	185.45	15.36%
Part2	271.19	-224.11	236.12	449.61	186.52	15.56%
Part3	181.41	-86.26	102.29	445.94	186.33	26.59%

Table 74: Results of MRP model with capacity constraint and four-week update in over-estimated scenario

Part1	225.51	131.49	0.39	157.50	64.17	98.38%
Part2	357.79	202.30	0.39	173.40	68.44	98.92%
Part3	226.19	143.14	0.15	169.16	66.57	99.42%

4.2.2.2.7 MRP with recourse constraint

As in the DRS model, we introduce the recourse constraint into the basic MRP model. As discussed in the previous section, we use the capacity upper bound of each part type as the signal to trigger a second shift. Each day, we check the daily production release plan based on the basic MRP model. If the release plan is greater than the capacity upper bound, a second shift is triggered. Intuitively, the performance should improve. In this case, we also build the model for all three scenarios with three different update frequencies.

Tables 75-77 show the results for the three scenarios under a one-week updating frequency. The comparison among the three scenarios is similar as in the basic MRP model.

- In the base scenario, the recourse constraint results in a slightly lower cycle time, hence slightly lower backorder, higher inventory and fill rate.
- In the under-estimated scenario, recourse constraint results in a much lower cycle time, hence much lower backorder, higher inventory and fill rate. When the production requirements are more than the forecast, the recourse model is effective in reducing the cycle time.
- In the over-estimated scenario, there is no obvious difference between the basic model and the model with the recourse constraint. Because there is no excess production when actual demand is lower than forecast, the system seldom triggers the second shift.

Table 75: Results of MRP model with recourse constraint and one-week update in base scenario

Part1	207.07	70.26	5.05	205.85	83.59	87.37%
Part2	328.72	106.85	6.92	221.38	87.23	88.14%
Part3	211.53	92.76	1.79	217.67	86.40	94.40%

Table 76: Results of MRP model with recourse constraint and one-week update in under-estimated scenario

Part1	201.73	-111.11	124.73	426.24	180.99	24.69%
Part2	320.77	-166.29	186.79	441.53	182.14	24.90%

Part3	206.96	-55.86	79.17	437.23	182.18	37.54%

Table 77: Results of MRP model with recourse constraint and one-week update in over-estimated scenario

Part1	212.41	117.25	0.26	159.25	65.10	98.74%
Part2	335.88	177.38	0.24	176.25	70.39	99.00%
Part3	215.42	131.11	0.05	171.80	67.86	99.72%

Tables 78-80 show the results for the three scenarios under two-week updating frequency. The comparison among the three scenarios is similar as in the basic MRP model. The comparison between the basic model and the recourse constraint model is similar to the one-week update model comparison.

Table 78: Results of MRP model with recourse constraint and two-week update in base scenario

Part1	203.85	68.30	5.87	202.76	83.17	85.86%
Part2	326.11	108.47	7.80	217.95	86.51	87.31%
Part3	209.71	92.92	1.98	214.34	85.97	93.67%

Table 79: Results of MRP model with recourse constraint and two-week update in under-estimated scenario

Part1	193.37	-83.26	98.81	377.05	156.67	27.77%
Part2	310.09	-121.64	144.87	391.34	158.04	27.91%
Part3	201.44	-30.89	57.61	386.93	158.36	42.59%

Table 80: Results of MRP model with recourse constraint and two-week update in over-estimated scenario

Part1	215.53	120.45	0.25	158.91	64.30	98.72%
Part2	341.90	183.90	0.34	175.06	69.00	98.89%
Part3	218.21	133.71	0.06	171.78	67.20	99.61%

Tables 81-83 show the results for the three scenarios under four-week updating frequency.

Table 81: Results of MRP model with recourse constraint and four-week update in base scenario

Part1	203.08	72.83	5.64	195.44	79.06	85.80%
Part2	322.32	110.91	7.47	211.67	83.32	86.88%
Part3	207.66	94.73	2.17	207.60	81.87	93.32%

Table 82: Results of MRP model with recourse constraint and four-week update in under-estimated scenario

Part1	178.14	-68.68	85.43	335.01	144.21	29.82%
Part2	288.37	-97.53	123.16	350.77	146.51	31.17%
Part3	188.88	-17.53	46.91	344.51	145.86	46.90%

Table 83: Results of MRP model with recourse constraint and four-week update in over-estimated scenario

Part1	225.03	129.79	0.33	158.70	63.80	98.48%
Part2	356.47	199.08	0.45	174.50	68.16	98.83%
Part3	226.43	142.99	0.09	170.33	66.51	99.48%

4.2.3 Conclusions

We summarize the comparison results for the multiple-machines case. We first compared the simulation results to those obtained via some analytical tools (i.e. MPA, RAQS and LPST) and they match well. This tells us that analytical tools are useful planning tools. Then we built the DRS and MRP models under different scenarios (i.e. base scenario, under-estimated scenario and over-estimated scenario).

We focus on two performance measures for the comparison, inventory position representing the cost, and fill rate representing customer service. Table 84 shows the aggregate results for the three parts for the base scenario under different policies. Here the MRP models are all based on one-week updating frequency. We find that:

- CONWIP constraint model obtained lower average fill rate and higher average inventory level than the basic DRS model, while CONWIP and recourse constraints obtained the highest fill rate and relatively low inventory level among all the models. From this example, we can say that CONWIP is not necessarily an effective way to improve the performance, but an effective way to provide recourse constraints.
- Compared to the basic MRP model, makespan constraint does improve the performance by increasing the fill rate and decreasing the inventory. The capacity constraint improves the fill rate but with higher inventory. The recourse constraints results in higher fill rate and higher inventory.
- Comparing all the models, the DRS with CONWIP and recourse constraints obtain the highest fill rate and relatively low inventory which is only higher than DRS basic model. Even the DRS basic model obtains a higher fill rate and lower inventory level than all the MRP models, which could be treated as a better performing model.

Table 84: Results for the base scenario under different policies

DRS	**89.72%**	**218.77**
DRS CONWIP	80.34%	218.79
DRS CONWIP Recourse	**91.83%**	**218.79**
MRP	88.49%	222.85

MRP Makespan	**88.70%**	**222.77**
MRP Capacity	89.00%	223.05
MRP Recourse	**89.45%**	**225.22**

Table 85 compares the results among basic DRS model and basic MRP models with different updating frequency. We find that:

- In the base scenario, where the actual demand arrival rate follows a Poisson distribution, the DRS model obtains the highest fill rate and relatively low inventory level, which is only higher than the MRP model with a 4-week updating frequency. We find that the MRP model with a 1-week updating frequency obtains the highest fill rate and inventory level. If we update more frequently, then the released plan can be adjusted to be closer to the actual demand.
- In the under-estimated scenario, the fill rate in all the DRS and MRP models dropped dramatically because of the high bottleneck resource utilization. However, the DRS obtained the highest fill rate. A comparison among the MRP models with three different updating frequencies follows the same pattern as in the base scenario, but the scale is larger than in the base scenario.
- In the over-estimated scenario, the fill rate in all the DRS and MRP models were rather high. The DRS model had the highest fill rate and lowest inventory, which indicates the best performance among all the models. When the MRP models with different updating frequencies are compared, we see the same pattern as in the base scenario for the fill rate, but the scale is smaller. However the inventory pattern is the opposite of fill rate. The MRP with 1-week updating frequency resulted in the best performance among all the MRP models.

- Overall, the DRS model obtained better fill rate than MRP in the base and under-estimated scenarios. DRS had better fill rate and inventory level than the MRP model in the over-estimated scenario. Among MRP models (base and under-estimated scenarios), the 1-week update frequency had the highest fill rate and inventory. In the over-estimated scenario, the 1-week update frequency had the highest fill rate and lowest inventory. Thus update frequency affects the MRP performance along with the forecast error.

Table 85: Results for basic DRS model and basic MRP models with different updating frequency

[redacted]	Base Scenario		Under-estimated Scenario		Over-estimated Scenario	
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	[redacted]
DRS	**89.72%**	**218.77**	**37.23%**	**218.80**	**99.19%**	**218.79**
MRP 1wk	88.49%	222.85	26.86%	216.48	99.12%	230.46
MRP 2wks	**87.21%**	**219.05**	**21.51%**	**204.93**	**99.01%**	**234.05**
MRP 4wks	84.50%	216.20	20.55%	185.62	98.94%	243.26

CHAPTER 5 CONCLUSION

In this thesis, we compare a relatively new production strategy, Dynamic Risk-based Scheduling (DRS) developed by Factory Physics Inc., with the traditional MRP-based strategies.

We first provide a review of the literature on different production scheduling systems. Then we discuss the theoretical models of the DRS and MRP-based scheduling systems. Later on we discuss the development of the simulation models for different systems we compare. Then we design a set of experiments to compare the performance between different strategies under different situations. This is the main contribution of this thesis.

In the experiment design part, we begin with a single-machine example. We compare the performance between MRP and DRS for varying levels of uncertainty in forecast demand (i.e. base scenario, under-estimated scenario and over-estimated scenario) and different levels of variability in the system (i.e. moderate variability and without variability). We find that:

- In the system with moderate variability, the DRS model had better performance than the MRP model in terms of: 1) higher fill rate and lower inventory in the base scenario; 2) higher fill rate with slightly higher inventory in under-estimated scenario; 3) much lower inventory with slightly lower fill rate in over-estimated scenario.

- In the system without variability, the DRS model had better performance than the MRP model in terms of: 1) higher fill rate and much lower inventory in the base scenario; 2) much higher fill rate and slightly higher inventory in under-estimated scenario; 3) higher fill rate and much lower inventory in over-estimated scenario. In addition, the DRS model obtained similar performance under the three scenarios which tells us that DRS model is more robust to forecast error.

When the experiment is extended to the multiple-machines case, we introduce more constraints into both the DRS and MRP models to improve their performance. The constraints are CONWIP, makespan, capacity, and recourse. We also test the performance of the MRP models under different updating frequencies. We find that:

- CONWIP by itself is not an effective way to improve the system performance, but an effective way to obtain recourse constraints.
- Introducing makespan, capacity or recourse constraints into the basic MRP model does improve its performance, but the DRS model with CONWIP and recourse constraints yields better performance.

REFERENCE

Benton, W., and Shin, H. (1998). "Manufacturing planning and control: The evolution of MRP and JIT integration." *European Journal of Operational Research*, 110(3), 411-440.

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

Bonvik, A. M., Couch, C. E., and Gershwin, S. B. (1997). "A comparison of production-line control mechanisms." *International Journal of Production Research*, 35(3), 789-804.

Buzacott, J. A. (1989). "Queueing models of kanban and MRP controlled production systems." *Engineering Cost and Production Economics*, 17, 3-20.

Chase, R. B., Aquilano, N. J., and Jacobs, F. R. (1998). *Production and Operations Management: Manufacturing and Services*, Irwin/McGraw-Hill.

Cheng, T. C. E., and Podolsky, S. (1996). *Just-in-Time Manufacturing: An Introduction*, Kluwer Academic Publishers.

Cheraghi, S. H., and Dadashzadeh, M. (2008). "Comparative Analysis Of Production Control Systems Through Simulation." *Journal of Business & Economics Research*, 6(5).

Damodaran, P., and Melouk, S. (2002). "Comparison of push and pull systems with transporters: a metamodelling approach." *International Journal of Production Research*, 40(12), 2923-2936.

Deleersnyder, J. L., Hodgson, T. J., King, R. E., O'Grady, P. J., and Savva, A. (1992). "Integrating kanban type pull systmes and MRP type push systems: insights from a markovian model." *IIE Transactions*, 24(3), 43-56.

Enns, S. T. (2001). "MRP performance effects due to lot size and planned lead time settings." *International Journal of Production Research*, 39(3), 461-480.

Framinan, J. M., González, P. L., and Ruiz-Usano, R. (2003). "The CONWIP production control system: review and research issues." *Production Planning & Control*, 14(3), 255-265.

Geraghty, J., and Heavey, C. (2004). "A comparison of Hybrid Push/Pull and CONWIP/Pull production inventory control policies." *International Journal of Production Economics*, 91(1), 75-90.

Grasso, E. T., and Taylor, B. W. (1984). "A simulation-based experimental investigation of supply/timing uncertainty in MRP systems." *International Journal of Production Research*, 22(3), 485-497.

Guide, V. D. R., and Srivastava, R. (2000). "A review of techniques for buffering against uncertainty with MRP systems." *Production Planning & Control*, 11(3), 223-233.

Herer, Y. T., and Masin, A. M. (1997). "Mathematical programming formulation of CONWIP based production lines; and relationships to MRP." *International Journal of Production Research*, 35(4), 1067-1076.

Ho, C. J., and Ireland, T. C. (1998). "Correlating MRP system nervousness with forecast errors." *International Journal of Production Research*, 36(8), 2285-2299.

Hodgson, T. J., and Wang, D. (1991). "Optimal hybrid push/pull control strategies for a parallel multistage system: Part II." *International Journal of Production Research*, 29(7), 1453-1460.

Hopp, W., and Spearman, M. (2004). "Commissioned Paper To Pull or Not to Pull: What Is the Question?" *Manufacturing & Service Operations Management*, 6(2), 133-148.

Hopp, W., and Spearman, M. (2008). *Factory physics*, Irwin/McGraw-Hill Boston.

Huang, C. C., and Kusiak, A. (1996). "Overview of Kanban systems." *International Journal of Computer Integrated Manufacturing*, 9(3), 169-189.

Huang, M., Wang, D., and Ip, W. H. (1998). "A simulation and comparative study of the CONWIP, Kanban and MRP production control systems in a cold rolling plant." *Production Planning and Control*, 9(8), 803-812.

Kamath, M., Sivaramakrishnan, S., and Shirhatti, G. "RAQS: A software package to support instruction and research in queueing systems." 944-953.

Karmarkar, U. (1989). "Getting control of just-in-time." *Harvard Business Review*, 89(5), 122-130.

Karmarkar, U. (1991). "Push, Pull and Hybrid Control Schemes." *Tijdschrift voor Economie en Management*, 26, 345–363.

Koh, S. C. L., Saad, S. M., and Jones, M. H. (2002). "Uncertainty under MRP-planned manufacture: review and categorization." *International Journal of Production Research*, 40(10), 2399-2421.

Krajewski, L., King, B., Ritzman, L., and Wong, D. (1987). "Kanban, MRP, and shaping the manufacturing environment." *Management Science*, 33(1), 39-57.

Krupp, J. (1984). "MRP Failures and the Purchasing Interface." *Journal of Purchasing and Materials Management*, 20(2), 18-21.

Lambrecht, M., and Decaluwe, L. (1988). "JIT and constraint theory: the issue of bottleneck management." *Production and Inventory Management*, 29(3), 61-65.

Lee, T. S., and Adam, E. E. J. (1986). "Forecasting error evaluation in material requirements planning(MRP) production-inventory systems." *Management Science*, 32(9), 1186-1205.

Little, J. D. C. (1961). "A Proof of the Queueing Formula $L = \lambda W$." *Operations Research*, 9, 383-387.

Luss, H. (1989). "Synchronized manufacturing at final assembly and feeder shops." *International Journal of Production Research*, 27(8), 1413-1426.

Meng, G., and Heragu, S. (2004). "Batch size modeling in a multi-item, discrete manufacturing system via an open queuing network." *IIE Transactions*, 36(8), 743-753.

Mitra, D., and Mitrani, I. (1990). "Analysis of a Kanban discipline for cell coordination in production lines. I." *Management Science*, 36(12), 1548-1566.

Mohan, R., and Ritzman, L. (1998). "Planned Lead Times in Multistage Systems." *Decision Sciences*, 29(1), 163-191.

Monden, Y. (1983). *Toyota Production System: Practical Approach to Production Management*, Engineering & Management Press, Norcross, GA.

Nahmias, S. (2001). *Production and Operations Analysis*, Jeffrey Shelstad.

Ohno, T. (1988). *Toyota Production System: Beyond Large-Scale Production*, Productivity Press, Cambridge, MA.

Orlicky, J. (1975). "MRP: The New Way of Life in Production and Inventory Management." New York: McGraw-Hill.

Ovalle, O. R., and Marquez, A. C. (2003). "Exploring the utilization of a CONWIP system for supply chain management. A comparison with fully integrated supply chains." *International Journal of Production Economics*, 83(2), 195-215.

Pandey, P. C., and Khokhajaikiat, P. (1996). "Performance modeling of multistage production systems operating under hybrid push/pull control." *International Journal of Production Economics*, 43(2-3), 115-126.

Pyke, D. F., and Cohen, M. A. (1990). "Push and pull in manufacturing and distribution systems." *Journal of Operations Management*, 9(1), 24-43.

Rees, L. P., Huang, P. Y., and Taylor, B. W. (1989). "A comparative analysis of an MRP lot-for-lot system and a Kanban system for a multistage production operation." *International Journal of Production Research*, 27(8), 1427-1443.

Siha, S. (1994). "The pull production system: modelling and characteristics." *International Journal of Production Research*, 32(4), 933-949.

Silver, E. A., and Meal, H. C. (1973). "A heuristic for selecting lot size quantities for the case of a deterministic time-varying demand rate and discrete opportunities for replenishment." *Production and Inventory Management*, 14(2), 64-74.

Spearman, M. L., Woodruff, D. L., and Hopp, W. J. (1990). "CONWIP: a pull alternative to kanban." *International Journal of Production Research*, 28(5), 879-894.

Spearman, M. L., and Zazanis, M. A. (1992). "Push and pull production systems: issues and comparisons." *Operations Research*, 40(3), 521-532.

Uzsoy, R., and Martin-Vega, L. A. (1990). "Modelling Kanban-Based Demand-Pull Systems: A Survey and Critique." *Manufacturing Review*(3), 155-160.

Wang, D., and Xu, C. G. (1997). "Hybrid push pull production control strategy simulation and its applications." *Production Planning and Control*, 8(2), 142-151.

Wemmerlov, U. (1986). "A time-phased order-point system in environments with and without demand uncertainty: a comparative analysis of non-monetary performance variables." *International Journal of Production Research*, 24(2), 343 - 358.

Whitt, W. (1983). "The Queueing Network Analyzer." *Bell System Technical Journal*, 62(9), 2779-2815.

Whybark, D. C., and Williams, J. G. (1976). "Material requirements planning under uncertainty." *Decision Sciences*, 7(4), 595-606.

Wight, O. W. (1995). *Manufacturing Resource Planning: MRP II: Unlocking America's Productivity Potential*, John Wiley and Sons,.

Yavuz, I. H., and Satir, A. (1995). "Kanban-based operational planning and control: simulation modelling." *Production Planning & Control*, 6(4), 331-344.

Yeung, J. H. Y., Wong, W. C. K., and Ma, L. (1998). "Parameters affecting the effectiveness of MRP systems: a review." *International Journal of Production Research*, 36(2), 313-332.

Zais, A. (1986). "IBM reigns in dynamic MRP II marketplace." *Computerworld*, January 27, 37.

GLOSSARY OF TERMS

MRP: Material Requiements Planning

MPS: Master Production Schedule

DRS: Dynamic Risk-based Scheduling

MRP II: Manufacturing Resources Planning

ERP: Enterprise Resource Planning

APO: Advanced Planning Optimization

JIT: Just-In-Time

WIP: Work-In-Process

CONWIP: Constant WIP

ROP: Reorder Point

ROQ: Reorder Quantity

LPST: Lean Physics Support Tool

MPA: Manufacturing systme Performace Analyzer

RAQS: Rapid Analysis of Queueing Systems

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