ANALYSIS OF TOOL SCHEDULING STRATEGIES IN A STOCHASTIC ENVIRONMENT WITH A FINITE LIFE RESOURCE

By

Steven B. Lyman

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ABSTRACT

ANALYSIS OF TOOL SCHEDULING STRATEGIES IN A STOCHASTIC ENVIRONMENT WITH A FINITE LIFE RESOURCE

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Tooling has become a growing concern in most manufacturing environments. This is most apparent in environments which have eliminated inventory and capacity buffers which hide problems. Tooling is often the main determinate of shop floor capacity and performance. The recognition of tooling as a finite life resource has brought about this research which involves tool control.

While there is an extensive body of research which examines machine and labor resources, neither emulate tooling. Past dual resources constraint (DRC) research examines only machine and labor as infinite life resources. The unique nature of tooling necessitates the need for control and scheduling procedures which considers these differences. Specifically, the unique traits of tooling are, machine specific because of size, finite life, and can be refurbished (maintenance).

The purpose of this research is to examine how a finite life resource, which has maintenance performed intermittently, should be controlled. How should a DRC flow shop, with a finite life resource, be controlled when both tool life and maintenance time are characterized by a stochastic distribution ill be addressed. The DRC model used in this simulation research attempts to answer this question by examining the scheduling of jobs and control of tools.

Output from this model was analyzed using ANOVA and Tukey multiple comparisons. The analysis found that tool control was the dominate factor in determining shop performance, followed by job scheduling. How tools were controlled, via maintenance, determined tool availability which influenced shop performance. Those tool rules which promoted frequent preventive maintenance over that of corrective maintenance enhanced performance.

As for job scheduling, job priority rules (dispatching) were most influential on due date performance measures. Job priority rules which prioritized by sequence dependency over considering all job due dates performed worse. While this result contradicts past research, it can be attributed to the finite life of tooling.

DEDICATED TO MY WIFE

CAROL LYNN REWERS

THANK YOU

ACKNOWLEDGEMENTS

I wish to thank several individuals who provided assistance and support during my dissertation process. Professor Steven A. Melnyk, Chairman of the Dissertation Committee, was instrumental throughout the dissertation. He provided direction, support, input, and most of all motivation. His knowledge and accessibility have added innumerable to the completion of this dissertation. A sincere thanks for all he has done.

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Lastly, I would like to thank the members of my family, both my parents, Richard and Irma Lyman, and my in-laws, Leonard and Doris Rewers. Without their support, encouragement, and patience, both the Ph.D. program and dissertation would not have been possible.

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TABLE OF CONTENTS

CH

BI

1-1
1-2
1-3
4-1
4-2
4-3
4-4
4-5
5-1
5-2
6-1
6-2
6-3
6-4

6-5
6-6
6-7
6-8
6-9
6-10
6-11
6-12
6-13
6-14a

6-14b

6-14c

6-14d

6-14e

6-14f

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND PROBLEM STATEMENT

1.1 INTRODUCTION

Control systems such as Just-In-Time (JIT) and Computer Integrated Manufacturing (CIM) have eliminated buffers in manufacturing environments, including work in process and excess capacity. With fewer buffers, tooling has a greater effect on production performance (Mason, 1986) such as delay order processing. Tooling has become a major issue in most manufacturing environments. In a Flexible Manufacturing System (FMS) for example, machining center flexibility is determined by the number of different tools in the storage magazine (Gray, Seidmann and Stecke, 1986). FMS tooling is a critical resource that needs special control procedures (Gruver and Senninger, 1990).

In the automotive industry (Vasilash, 1990) and in other repetitive manufacturing environments, the concern over tooling centers on costs. As much as 20 percent of a firm's material costs (Erhorn, 1983) can be attributed to tooling. In the case of FMS, an estimated 25 to 30 percent of fixed and variable costs are due to tooling (Kouvelis, 1991). Annual costs for various forms of tooling can exceed \$1 Million for small firms and \$100 million for large firms (Huber, 1989). The U.S. metalworking industry spends an estimated \$1.5 billion a year on cutting tools alone (Mason, 1991). As firms strive to utilize assets more effectively, tooling issues take on greater importance. Idle or unused resources are a drain on assets and

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and profits. Effective tooling asset management requires the right tool at the right machine. Without adequate control, machines and workers are idle, and schedules and delivery dates are missed (Kupferberg, 1986).

As the study of shop floor control focuses more on tooling its effect on performance becomes apparent, particularly with respect to capacity (Kupferberg, 1986; Blackburn, 1989). Tooling is often the main determinant of shop floor capacity. Up to 16 percent of production schedules (Mason, 1991) may be missed because of such problems as insufficient tool life, lost tools, and tool failure.

The importance of tooling was also confirmed during two separate interviews. In the first case, an automotive parts supplier was in the process of developing a fully integrated automated tool control system to monitor all forms of tooling. The tool control system will be a key component in a new production plant beginning operation soon. The supplier had decided to invest in the new system for three reasons.

First, to satisfy customer due date (delivery dates). In the past, the supplier had not monitored tool wear and maintenance, resulting in unscheduled down time and missed delivery dates. With the adoption of JIT by the supplier's customers, lost capacity due to tooling can no longer be tolerated.

Second, some customers believe that properly maintained tools can provide a better quality product. Research has shown that well-maintained tools not only yield higher quality products but also ensure reliable capacity (Finch and Gilbert, 1986). Since the supplier had no record of scheduled maintenance, the customer questioned whether the supplier was capable of maintaining quality tolerances for products.

Third, the supplier estimated that each plant operation had up to $25 million in obsolete or unusable tools stored throughout the plants. Another cost factor involved buffers, as noted earlier. When the supplier moved to reduce inventory cost by lowering work in process and excess tooling, it became apparent that controls were necessary to plan tooling use and maintenance. It also became apparent that the scheduling of tooling for production was a function of required maintenance and differs from the traditional procedures used for machines and equipment. The variability of tool types (both cutting and forming) contributed to uncertainty, and the supplier had to reevaluate and develop new policies for controlling tools.

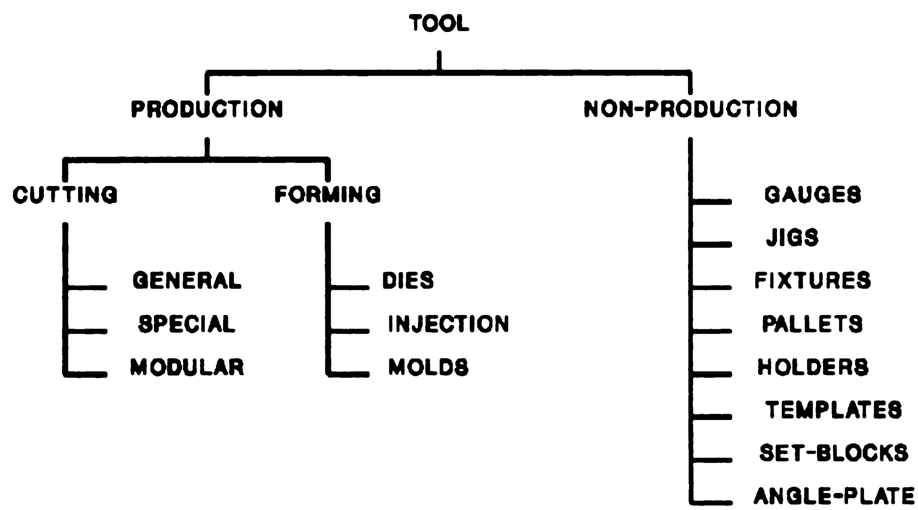
In the second case, the researcher interviewed a firm supplying consumer products and discovered similar problems. The manager had adopted modular tools to cut tooling cost, up to 40 percent. The modular tools allowed the firm to make variations of its products using the same tool by inserting or moving sections on the tool. The new tools increased flexibility, but reduced tool life and increased required maintenance. This in turn, caused problems in tool availability and production scheduling. New policies had to be adopted to control for those contingencies.

As these cases illustrate, tooling is a constraining resource long overlooked by production managers. With the adoption of JIT and other new approaches, it has become apparent that tooling is a key component of manufacturing that companies no longer can afford to ignore.

1.2 DESCRIPTION OF TOOLING ENVIRONMENT

Briefly, tooling is composed of a variety of items which include: jigs, fixtures, forms, dies, cutting tools, gauges, molds, templates, and more (Broom, 1967). Figure 1-1 shows the various forms of tooling. There are production and

Figure 1-1 Tool Taxonomy



non-production tools, differentiated by the fact that production tools are those used to shape or alter the product directly.

Table 1-1 compares different tool types on a number of dimensions. For example, costs for a standard cutting tool (drills) are low, specialized cutting tools (multi-bit mill) are moderate (up to $10,000), and costs for dies are high ($100,000 and up). It should be noted that a number of the dimensions are interrelated such as replacement frequency and life of tool.

Table 1-1 Comparative Rating of Tooling Issues by Tool Type

	Tool Type			
Tooling Issues	Standard Cutting	Special Cutting	Stamping Dies	Injection Dies
Costs per Tool	Low	Moderate	High	High
Purchasing Lead Time	Low	Low	High	High
Tool Standardization	High	Moderate	Low	Low
Life of Tool	Low	High	High	High
Breakage Probability	High	Moderate	Moderate	Moderate
Breakage Cost	Low	Low	High	High
Maintenance Frequency	High	High	Moderate	Moderate
Maintenance Lead Time	Low	Low	Moderate	Moderate
Replacement Frequency	High	Moderate	Low	Low
Replacement Lead Time	Low	Low	High	High
Speed Variability	High	High	Low	Low
Scheduling Difficulty	Low	Low	High	High
Duplicates Likely	High	Moderate	Low	Low
Batch Run Length	Low	Low	High	High

As can be seen in Figure 1-1, production tools fall into two categories, cutting or forming and it is this latter category which is of interest in this research. Forming tools have two important features: cost and uniqueness. It is not uncommon for forming tools to cost as much as the machine on which it is used (Brown, Geoffrion and Bradley, 1981), in excess of $1 million and for that reason multiple

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multiple tool copies are rare. The single tool copy places a capacity constraint on the jobs produced and is especially apparent when the tool requires maintenance. When a forming tool breaks or needs service, it is pulled for repair, and unlike cutting tools, can not be easily replaced with a new copy.

1.2.1 Tool Life

A major variable in the production environment is tool life. Tool life is defined as: the period between placing a tool into production and removing it from service because it no longer yields a quality (usable) product. Once the tool fails to make a quality part, it must be refurbished or repaired. Obviously, tool life is directly related to control and scheduling of both production and maintenance.

A unique difference between cutting and forming tools is that the latter are not discarded until a model change makes them obsolete. Depending on their classification, forming tools generally do not wear out permanently. The classification of forming tools found in the *Tool Engineers Handbook* (1949) is shown in Table 1-2. This research centers on the type A classification.

During the life of a forming tool there may be several refurbishment or maintenance operations. In this research, tool life is defined as the period between placing a tool into production and removing it from service for maintenance. Tool life is a finite life resource because there will be periods when the tool is unavailable for production. The fact that tools are not always available for production and the subsequent impact on capacity has been noted by researchers

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Table 1-2 Forming Tool Classifications.

Class	Description of Classification
A	Best type and grade of materials used for long life. Designed for high volume production and for ease of maintenance.
B	Applicable for medium production quantities. Designed to last for total production run only. Less consideration given to ease of maintenance.
C	Cheapest useable tools for low volume production. Limited life with little or no maintenance done on tool.
Temporary	Used for limited production runs typically found in job shops. Lowest cost tool that can produce the part.

Source: Tool Engineers Handbook, 1949

1.2.2 Tooling Traits

Tooling differs from other production resources because tools: (1) are specific to machines and jobs, (2) have a finite life, and (3) are renewable (Melnyk, Ghosh and Ragatz, 1989). Some of these traits were mentioned previously, and are now described in detail.

1) Specificity: Tools usually are used on a designated machine because of size or configuration. Frequently, the machine is the only resource capable of using the tool for production. Use on a designated machine also simplifies shop floor control, as the tool may be too large to transport, and use at one location simplifies the flow of production. Compared to cutting tools forming tools tend to be more machine specific.

Another aspect of specificity involves the specific tasks of each job or order. Cutting tools usually are flexible, that is, different types such as reamers and mills can perf

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can perform the same production task (Slack, 1987). In reality, this flexibility is limited because job's require certain production tasks by certain tools. The advantage of cutting tools are that multiple tool copies exist for each tool type. The tooling requirements of a given job may be fulfilled by any copy of a specific tool type. With forming tools, there exists only one copy of each tool, and it is designed for a particular product or job.

Thus, forming tools are both machine and job specific. A tool is used on one machine and is used to process a single job type. Introducing machine-specific tooling is a unique approach to production simulation.

2) Finite Life: Recall that tool life is defined as the period during which the tool yields a usable product (from placement into production until removal for maintenance). Various measures for defining tool life include number of hours of operation, number of jobs processed, or number of tool hits (McCall, 1965; Gillimore and Penlesky, 1988). Finite life means that the tool is a resource which may not always be available. Past research with either machine, labor, or a combination of the two assumes that tools will always be available (Nelson, 1967; Fryer, 1974; Treleven and Elvers, 1985). The worker or machine does not wear out and is assumed to have a infinite life, whereas finite life tooling must be removed at the end of its life. When the tool fails to produce a usable product or reaches a point at which the risk of failure is high, it must be serviced. The removal for maintenance differentiates the tooling resource from the labor resource. It does, however, make tooling life similar to machine breakdown.

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3) Renewal: The frequency and duration of tool renewal varies with tool type. Cutting tools have a relatively shorter tool life and tend to require renewal more often than forming tools. The renewal processes for cutting tools involves sharpening which is usually short in duration (McCall, 1965). Due to forming tools size and intricacy, renewal maintenance requires more time which complicates production scheduling.

The renewal process involves either preventive or corrective maintenance (Pierskalla and Voelker, 1976). Corrective Maintenance (CM) takes place when a tool fails, (i.e. when it breaks or no longer yields quality products). Preventive Maintenance (PM) occurs before tool failure. As the frequency of PM is increased, the frequency of CM decreases as shown in Figure 1-2a. The figure indicates a linear relationship, but a nonlinear shape is possible.

PM is less costly and shorter in duration than CM (Sherif and Smith, 1981). It has been found that PM helps provide quality outputs at a lower operating cost than CM (Sutton, 1983). Figure 1-2b illustrates maintenance costs (PM plus CM) versus the costs of breakdown and associated penalties (Newman, 1985; Gallimore and Penlesky, 1988). As the level of maintenance increases, total costs decrease via lower failure costs. For each dollar invested in maintenance, failure costs drop by a greater amount up to a point when it is no longer advantageous to invest in additional maintenance. The intersection of the maintenance and failure cost curve is the point of lowest costs. Past the intersection, the costs and time consumed by maintenance exceed the benefits of reduced failure cost and down time. The

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Figure 1-2a Comparison of Maintenance Policies and Frequency of Occurrence

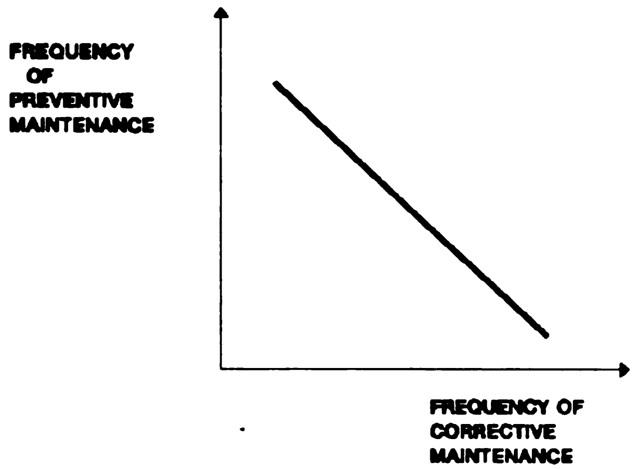
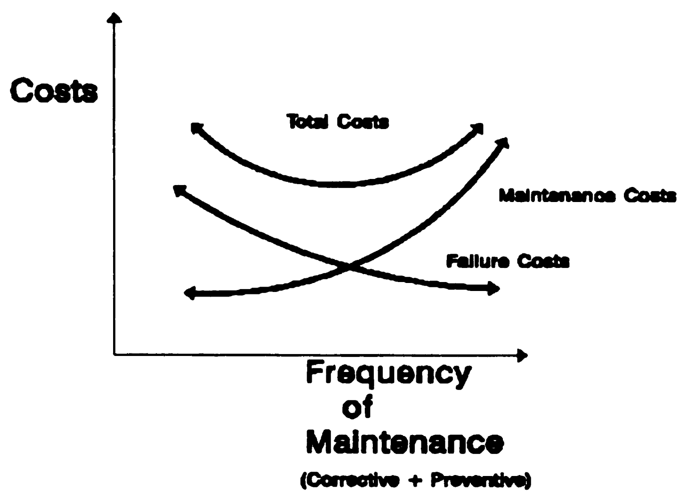


Figure 1-2b Comparison of Maintenance Frequency to Costs



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1.3 PROBLEM STATEMENT

The research question which will be answered is: **How do you effectively manage operations in a dual resource constraint shop where the tooling constraint has a finite life and where resource life and resource renewal are described using stochastic distribution?** Tooling has traditionally been viewed as a component of a machine. Machine specific issues examined in the past have assumed that results are applicable to both tool and machine. Some researchers and practitioners have come to realize that tools and machines are separate resources (Brown et al., 1981; Gray et al., 1989). Therefore, <u>this research examines tooling as a separate and constrained resource in addition to the machine resource</u>. Given that tools and machines are separate resources, methods to control each resource must be developed to enhance production shop performance. The model adopted here is a variation of previous work conducted in a dual resource constraint (DRC) job shop (Melnyk et al., 1989). A DRC job shop has two limited resources which influences its output. In this research, both tooling and machines must be available in order to process a job. This work also focuses on forming tools and the unique nature which affects the control procedures needed in the shop. The scheduling heuristic developed here will attempt to provide good (not optimal) performance, given the tooling attributes that cause system variance. It has been shown that shop performance can be improved by reducing components of variance within the system (Ma

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system (Melnyk, Denzler and Fredendall, 1992). One component of system variance is whether tooling is available when needed and whether the tool has sufficient life to process the job in its entirety. The other component of system variance is the time required to repair tools. The two forms of system variance will be modeled using stochastic distribution which emulates the real world environment.

With this in mind, more specific questions can be developed. The following are some of the questions from which hypotheses will follow.

1.3.1 <u>How do we schedule jobs?</u>

The objective of scheduling is to move jobs through the shop as quickly as possible. At issue is how to process jobs when each stage of the operation requires two resources, machine and tool. Since jobs are both machine and tool specific, if either one of these limited resources is unavailable, the job must remain in queue until both resources are free. Figure 1-3a illustrates the scheduling process. Job scheduling must consider machine condition (availability and setup), jobs in queue, and tool condition (availability and life). The rank order of jobs in the queue is based on priority, which is determined by four factors:

Job Priority = f(Job Traits, Job Interrelationship,
Tool Condition, Shop Condition).

The question of how to schedule jobs, focuses on issues related to the job with the highest priority. The determination of priority depends on certain conditions and types of information. The following discussion looks at each of the four factors wh

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Job traits refer to attributes specific to each job, such as job arrival, processing time, or job due date (Blackstone, Phillips and Hogg, 1983). The information is used in setting priorities for dispatching rules, which have been shown to improve shop performance (Conway, Maxwell and Miller, 1967). After several interviews with manufacturing companies, this researcher determined that due date dispatching rules are the predominant selection criterion. This held true whether sequence dependency was present or not.

Job interrelationship refers to traits common to a number of jobs in queue. The interrelationship of interest in this study is sequence dependency, that is, jobs requiring the setup (or tool) currently on a machine. The objective of sequence dependent job processing is to reduce the amount of time consumed by setup/tool changes. Jobs requiring the same setup/tool will be given higher priority.

Tool condition information help determine job priority on the basis of tool life and risk of tool failure. The issue involves tradeoffs between tool condition and job processing. Should a job be processed if the risk of tool failure is very high? If the processing time for a job exceeds the tool's estimated usable life (before maintenance), should it be processed? If so, under what criteria? The tradeoff involves whether to start processing the job with the possibility of delivering the job on time versus the risk of tool failure, causing added maintenance time and missed delivery. The consideration of tool condition in establishing job priority has not been addressed in the literature.

Figure 1-3a Information Flows Involved in Job Selection: Basic Model

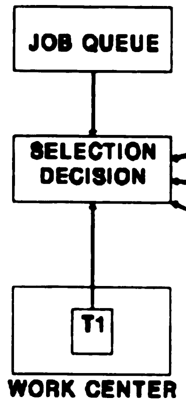
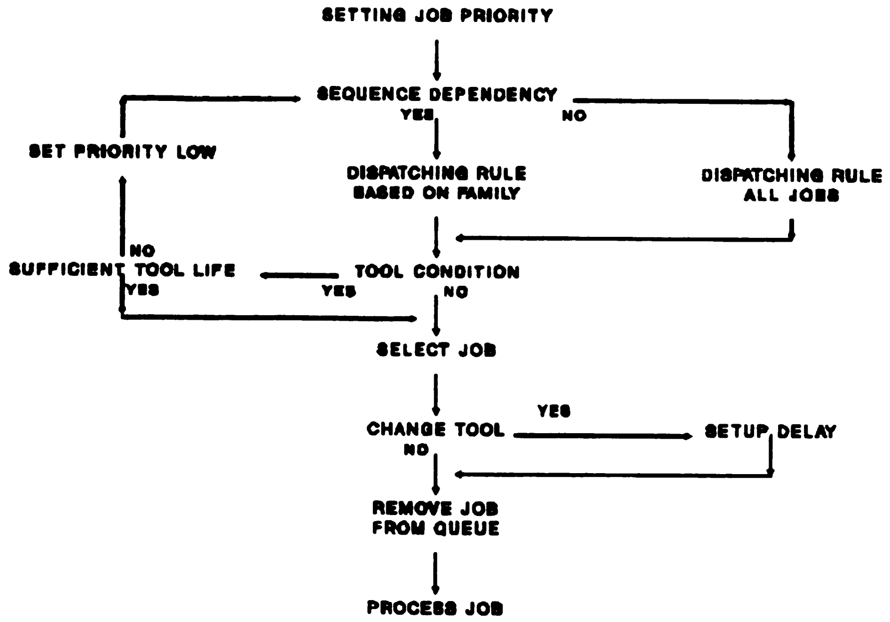


Figure 1-3b Information Involved in Job Selection: Decision Flow



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Shop condition refers to the status of the shop floor when determining priority. The idea is to examine the total shop condition before releasing work to the floor. Order Review Release (ORR) has been found to be beneficial to shop performance by leveling work load (Melnyk and Ragatz, 1989). The use of information for determining due dates has been examined by Bertrand (1983) and Baker (1984).

Figure 1-3b shows the decision process in setting job priority and selection. The exact sequence of decision can vary, but for the purposes of this model decisions will be made according to Figure 1-3b.

1.3.2 How do we schedule tools for production and maintenance?

This two part question is combined because the elements of production and maintenance are interrelated. Both production and maintenance requirements determine tool usage. More specifically, when to put a tool into production and when to pull it out. Four factors influence tool usage:

Tool Usage = f(Tool Condition, Demand for Tool, Demand for Other Tools, Maintenance Activity).

Tool condition determines whether a tool can continue in production. The tool is either usable or not. If not usable, it is then classified as a tool failure. A usable tool goes through different stages of life but by definition is still capable of processing jobs. The issue is whether there is sufficient life on the tool to process a job.

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Demand for tool refers to sequence dependency, that is, whether there is a high priority job in queue that requires the tool currently on a machine. A tool will remain in use as long as there are jobs that require it, except when truncation occurs (jobs of higher priority are placed in queue).

Demand for other tools arise when truncation requires a different tool setup. In other words, production of one item stops temporarily in order to produce a different item and a tool change takes place. Tool usage in this case is based on priority as compared to simple demand.

Maintenance activity relates to and uses information about tool condition. If a tool fails and needs CM, then tool usage is terminated and the tool is sent for servicing. Termination also occurs during PM. Pulling a tool from production for PM is a cloudy issue. Strict PM policies dictate that maintenance occurs at a specified time for a given tool, whereas less restrictive PM policies consider other factors, such as demand or job priority.

Maintenance activity also affects tool usage if the maintenance queue is long, which reduces tool availability for production. In PM scheduling, managers must decide whether to pull a tool before its specified time if the maintenance queue is short. That is, managers must weigh the advantages of a short servicing period against the disadvantages of unplanned downtime. The decision also must take into account any other tools slated for PM.

1.3.3 How does variation in resource life and renewal affect the scheduling and assignm

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System variation effects shop performance. Variation can be viewed in two different ways: type of distribution (gamma, log-normal, etc.) and degree of variation. The focus of this research will be on the degree of variation on tool life and maintenance service time. This will be accomplished by testing different levels of variance for the specific distributions mean value both for tool life and maintenance service time. The question of how job scheduling and tool control heuristics perform under different conditions can be examined. The objective of this question involves the robustness of control heuristic under different environmental test conditions. It is not the objective to find an optimal solution or single best heuristic. Certain heuristic performance may deteriorate faster or slower with either tool life or maintenance variance or their combination. Table 1-3 illustrates the levels of variance that each heuristic will be subjected to. The goal in testing heuristic robustness is to develop a framework for tool control.

Table 1-3 Relationship of Tool-Maintenance Variance

	LOW MAINTENANCE VARIANCE	HIGH MAINTENANCE VARIANCE
LOW TOOL LIFE VARIANCE	LOW-LOW	LOW-HIGH
HIGH TOOL LIFE VARIANCE	HIGH-LOW	HIGH-HIGH

1.3.4 Specific Research Questions

The previous sections explored general questions and procedural issues relevant

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relevant to this research. More specific questions will examine how control procedures compare under different conditions of variability. In particular,

1. Does additional information used when setting job priority for scheduling affect shop performance?
2. Does preventive maintenance enhance shop performance over corrective maintenance?
3. How does various preventive maintenance policies influence shop performance.
4. Does variance in tool life and maintenance time affect the relative performance of different job priority and tool control heuristics.

1.4 RESEARCH METHODOLOGY

The SIMAN 3.5 simulation package is used to model a flow shop environment with additional subroutines written in Fortran (Pegden, 1987). This method is necessary because of the inability to control conditions in a real production shop. An analytical model would not provide the necessary complexity required to simulate a DRC shop (Nelson, 1966; Treleven, 1989).

The experimental factors to be examined in Chapter 4, are:

- Job Priority Rules
- Tool Control Policies
- Distribution Variance for Tool Life

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The research is organized into three phases. Phase one involves model development of control rules and policies, based on interviews with several manufacturing firms. Phase two validates and verifies the simulation model. The run length and batch size will also be determined to assure independence and normality at this time. Phase three involves full factorial design for the experiment, including data collection and analysis for the performance measures.

1.5 RESEARCH CONTRIBUTION

This research examines an area that has received little attention. The model developed extends past work in the DRC shop and on maintenance scheduling by adding tool control. The model explicitly considers tool life and its variability in the shop environment, an effect not previously explored.

Several researchers have pointed to gaps in the literature. Melnyk et al. (1989) described aspects of tooling that are ripe for research, including the need for additional tool assignment rules and an analysis of tooling in a detailed shop environment. Ghosh, Melnyk and Ragatz (1991) point to the need to examine different tool traits, such as tool life. Browne, Boon and Davis (1981) emphasized the need to consider availability of tooling, among other resources, in developing scheduling rules. They found no research in the area of shop scheduling with a tooling resource.

In Figure 1-4, the shaded area of the diagram represents the least studied issue

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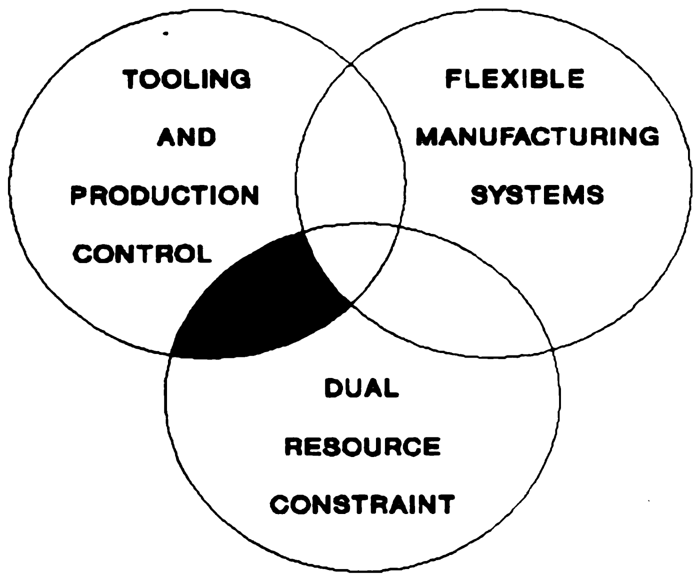
issues. Except for a few articles, research on tooling in the DRC shop model is insufficient. Only recently has the combined issue of FMS and tooling received much attention. Reasons for the FMS-tooling interest is the need to increase equipment utilization due to the expense of such an environment. Another reason for the interest lies in the adoption of JIT and waste elimination. As stated previously, when waste is curtailed, the effect of tooling becomes much more prominent.

Figure 1-4 Spheres of Research Focus



1.6 ORGANIZATION OF THE DISSERTATION

Chapter 2 examines past research, in particular the literature on tooling and the issues unique to this resource. Reviewed are articles on tool life, scheduling of tooling in

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tooling in FMS and job shop environments, and the effect of tooling on shop performance. Also examined is similarities to other DRC research such as labor in a DRC shop.

Chapter 3 presents a conceptual framework for tool management. An understanding of how tooling fits into production planning and shop floor control establishes a foundation for this research. Chapter 4 and 5 lays out the model in detail, including the hypotheses to be tested, the methodology, and the techniques used in testing the research hypotheses. This includes determining whether the data meets the required assumptions of various statistical techniques.

Chapter 6 presents the experimental results. This includes all statistical tests followed by a discussion of the results. The last part of chapter 6 point to future research directions and answers the questions developed in chapter 1.

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CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 INTRODUCTION

The issue of tool control received little attention until such methods as JIT began to eliminate buffers. The two buffers most relevant to tooling are inventory and capacity. Excess tooling is both a form of higher inventory cost and an unused capacity resource. With the increase in automation, the cost of under-utilization increases (Mason, 1991), as is evident in FMS. If tooling is unavailable, automated equipment cannot be used efficiently. Cost is another factor, as tooling can account for up to 30 percent of FMS cost. Several articles have pointed to the need to bring tooling into the mainstream of production control and research (Browne et al.,1981; and Melnyk et al, 1989).

This chapter focuses on the major tooling issues, including characteristics common to tooling and control. Recent studies address how tooling affects not just a single operation, but the whole shop. Gray et al. (1990) suggest the need to view tooling in a broader perspective because of its effect on FMS. Gray et al. (1990) propose a hierarchy ranging from tool-specific issues to the interrelationships of tools, scheduling, and system development.

The literature reviewed in this chapter addresses issues involving maintenance, sequence dependence, and DRC job shops. Much of this research lends credence to the values selected for parameters in this study and helps understand h

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understand how control procedures were derived. In examining the literature on DRC job shops, parallels and contrasts will be drawn between labor and tooling resources. This will assist in understanding how tooling control was developed and under what conditions.

2.2 TOOLING CHARACTERISTICS

2.2.1 Tool Types

The varieties of tooling and their applications were summarized previously in Figure 1-1, but was not all inclusive. According to Bloom (1967), tooling includes: fittings, chucks, micrometer rules, patterns, models, template setup tools, spring clamps, automatic ejectors, magazine feeders, steps and guides, slides, gauges, chutes, and tool sharpeners. These are just some of the different tools that are part of any production shop. The main components of tooling are those used in the direct transformation process, such as cutting tools, dies, and forms. The most common forms of tools are defined below.

There are power tools, hand tools, cutting tools, and setup tools. The first three are used to remove material from a product (chip removal). Examples are: drills, reamers, rasps, mill cutters, and grinders. Setup tools are used to prepare a machine (or power tool) for production. There are innumerable types and varieties of setup tools.

Dies - are metal patterned blocks that shape material through a stamping or vacuum process. Stamping dies typically are used to form metal parts and may invol

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involve a punching or cutting operation. Vacuum dies are used to draw flexible materials such as heated plastics over the die's pattern.

Molds - similar to dies, are used in forming a product. Injection molding forces molten plastic into molds with a specific pattern. Once the cavity within the mold is filled, the mold is cooled and the plastic solidified making the part(s).

Gauges - are used to measure some aspect of a manufactured part. Gauges are a common component of quality inspections. Gauges are used to determine whether parts meet tolerances.

Fixtures - are used to hold parts on a machine during processing.

Jigs - are used to hold and guide tools during the cutting/processing of a part.

Deis (1983) defines tooling as specific to a particular task. He suggests the same basic breakdown of tooling types and goes further to define tools as either special or general in their applications. The specialization or generalization of a tool is based on the breadth of the tools application. For example, special purpose tools are used for a specific task or order, whereas general application tools are more flexible in how, where, and on what it is used.

2.2.2 Tool Life

2.2.2.1 Description

A tool can be kept in production so long as it is capable of making parts that meet quality standards, a functional view first expressed by Taylor (1907). Tool life is related to machining economics, which correlates processing speed with rate of tool wea

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tool wear. An increase in cutting speed shortens tool life. Cook (1967) elaborated on this relationship by including cutting depth and temperature in the equation. As cutting depth increases, tool wear increases, and tool life is shortened. Furthermore, an increase in either cutting depth or speed raises the temperature, which can have a major effect on tools. High temperatures make tools more brittle and cause them to fail (break) more quickly. Cook also noted that tool vibration (chatter) affects tool life. As chatter increases, tool life tends to decrease.

Cook (1973) defined several determinates (criteria) for the length of time the tool remains in service. The first criteria, tool failure, consists of a fracture or breakage which makes the tool incapable of cutting. The second criteria involves dimensional tolerances. In this case, when a tool is no longer capable of maintaining product quality, it is no longer used. A tool may not be able to maintain the necessary tolerances long before it actually fails. The third criteria relates to the product surface. If their are abnormalities on a product surface, faster tool wear and shorter life may result.

Cook's final criterion relates to economic concerns. If a tool can be sharpened (reground), it may be advisable to remove it from production before it fails. An estimated average cost per cutting edge can be developed to determine what a tool's life should be. Given all these variables, tool life is not an exact science where predictions are accurate. Cook's (1973) basic formula for tool life includes several major variables.

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Where: T = tool life (min)

V = cutting speed (ft/min)

t = feed rate (in/rev)

b = depth of cut (in)

A,B,C,D = constants

This equation applies to cutting tools, about which there is extensive research. No similar work has been done on tool life estimations for forming tools. The reason lies in forming tools variation, complexity, and environment.

Based on Deis's (1983) definition, forming tools are classified as special purpose and tend to be complex. As the number of cutting edges, angle of bends, and number of parts (nuts and bolts) that compose a tool increases, the life of the tool decreases (Deis, 1983). This is based on the notion that as the number and complexity of parts on a product rise, so does the risk of product failure.

2.2.2.2 Tool Life Distributions

Initial research used deterministic distribution to estimate the life of a tool. Cook's (1973) equation has a set of parameters representing the environmental conditions encountered by a tool. The assumption is that if a cut is repeated under identical conditions, then the exact same tool life will be obtained for each tool used in that operation.

Fenton and Joseph (1979) argue that a deterministic tool life gives a distorted view of machining economics. Optimal policies under this assumption do not hold true whe

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true when stochastic tool life is used. Simulation results using stochastic tool life distributions show lower production and profits than with deterministic tool life distribution. The stochastic distributions tested include: normal, uniform and Weibull.

Bao (1980) studied multiple tool operations and drew the same conclusions as Fenton and Joseph (1979). Bao's research entailed having 2 - 6 tools operating at the same time versus a single tool. The probability of work stoppage is greater with a multi-tool operation because there are more tools that can fail. The operation is controlled by the tool with the greatest wear rate. Using three different stochastic distributions (log-normal, Weibull, and gamma) a dynamic programming model was developed for determining tool replacement policy. The results showed that the best policy is to replace all tools when the first tool wears out.

Several articles have analyzed a metal cutting process with multiple tools (Ramalingam, 1977; Ramalingam, Peng, and Watson et al., 1978; Ramalingam and Watson, 1978). The researchers found that tool failure was characterized by a Weibull distribution when single tool failure occurred. A gamma distribution was observed when multiple tool failure was presented, and a log-normal tool life was possible under certain conditions.

The distributions observed for cutting tools also apply to forming tools. The same distribution is also found in machine failure as between the two tool types (Lie, Hwang, and Tillman, 1977).

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2.2.3 Tooling Economics

The economics of processing is determined by two factors, tool life and speed. As processing speed increases, production output rises resulting in additional profit. Tool wear also increases, causing shorter tool life, frequent replacement, and higher costs.

A number of articles have examined this relationship (Hitomi, 1976a, 1976b; Levi and Rossetto, 1978; Rossetto and Levi, 1978; Ravignani, Zompi, and Levi, 1979; and Bon, 1980). An important component to these articles involve the determination of tool life. The more variable (stochastic) the distributions selected, the more frequent the need to replace tools and the lower the profit. When the machining environment involves multiple tools simultaneously, the replacement strategy worsens. The best policy is to replace all tools, when one fails. The benefit of replacing all tools simultaneously is that the total number of failures is reduced. The drawback is that some tools are replaced before their entire processing life is consumed.

2.2.4 Tooling Characteristic Summary

Figure 2-1 provides a taxonomy of tooling characteristics. The first part of this section defines the different types of tools and their basic functions (Bloom, 1967). Subsequent discussions centered on tool life. In particular, Cook (1973) described how tool life is affected by the cutting environment which is composed of cutting speed, depth, and temperature. Cook also developed a formula, based on

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Taylor's (1907), for calculating tool life based on these three main components.

When analyzing tool life and machining, both deterministic and stochastic distributions have been used to model tool life. Fenton and Joseph (1979) argued that deterministic distributions give an unrealistic view of the cutting environment. Using stochastic tool life distributions give lower cost performance values than deterministic distributions. Proper distribution selection also plays an important role when looking at the economics of processing. Tradeoffs must be made between processing speed and tool replacement costs (Levi and Rossetto, 1978). The faster work is processed, the more frequent the need for tool replacement.

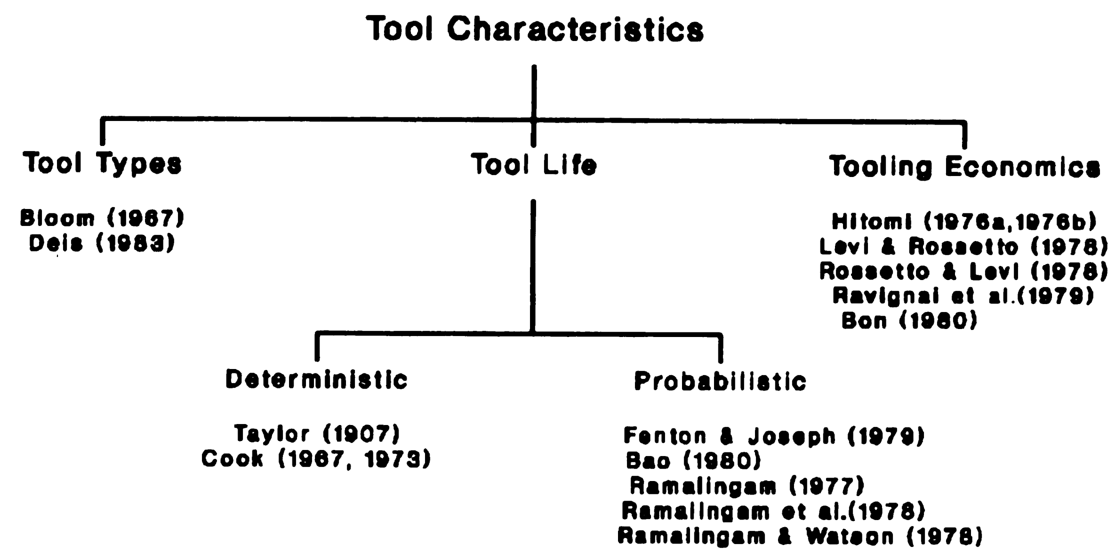
2.3 TOOL SCHEDULING

This section examines the broad set of literature which looks at the allocation of tooling resources. The tool scheduling process varies depending on the environment (FMS, DRC, or MRP) it is examined under. The variation can be attributed to shop layout and its associated hardware. An element common to all environments is that of tool characteristics, such as tool life.

2.3.1 Flexible Manufacturing Systems

Tooling is a major concern in a FMS environment because it accounts for 25 - 30 percent of the fixed and variable costs (Ayres, 1988). Kiran and Krason (1988) point out that tooling has a major effect on FMS performance and that on-line monitoring of tool wear is needed if performance is to be improved. Gruver and

Figure 2-1 Tooling Issues Taxonomy



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Scaninger (1990) also agree that on-line tool monitoring is essential if the benefits of FMS are to be fully realized. The main advantage of on-line monitoring are reduced down time and higher output levels (Kendall and Bayoumi, 1988). Articles by Gray et al. (1989, 1990) provide the most comprehensive examination of tooling issues and past research on FMS tooling. They also divide FMS tool control into three areas. These are shown in Figure 2-2, which is a hierarchical view of tool management in FMS.

2.3.1.1 FMS and Tool Characteristics

The major tool characteristics relevant to FMS are: tool life, cutting economics, standardization, and number and location of tools (data/information). Tool life already has been discussed, and suffice it to say that the tool life equation (Cook, 1973) and distribution issues (Ramalinjam, 1978) are the same in all cutting environments. What is unique is that FMS can monitor on-line tool wear and communicates this information throughout the system. The system can react automatically when a tool breaks or needs replacement (Turn and Tomizuka, 1989).

The second tool characteristic, cutting economics, is common to any cutting environment. Primrose and Leonard (1986) looked at the trade off between tools, materials, and labor costs in an effort to pinpoint variable processing costs.

McCarthey and Hinds (1982) considered demand due dates and processing speed in an FMS. In their model, the machines in the shop are initially set at maximum speed, and planned idle time allows process rates to be reduced so that no

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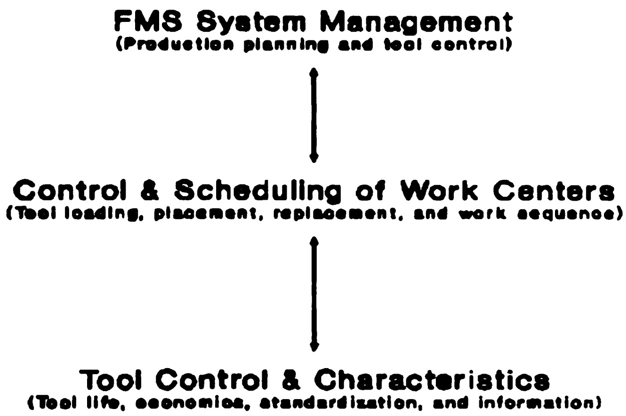
Figure 2-2 FMS Planning and Control Hierarchy
(Gray et al., 1989)



idle time remains. The objective is to process all jobs to meet due dates at the slowest processing time possible in order to limit tool wear and operating costs.

The third tool characteristic, standardization, while applicable to any environment is especially important in FMS because of the high cost of cutting tools (Ayres, 1988). By standardizing, fewer tools are needed, which means substantial savings in inventory and control costs (Hartley, 1984). Group technology techniques is one method proposed for finding tool commonality that leads to standardization (Burbridge, 1975; Chang and Wysh, 1985). Dushin, Jones, and Lowe (1990) developed an algorithm to find the smallest set of tools necessary to perform an operation, subject to an FMS tool magazine capacity.

The last tool characteristic issue important to FMS deals with data (number of duplicate tools and locations). Information is collected regarding tool wear, number, and location. Tool data is necessary at subsequent levels for replacement and tool

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and tool magazine loading. Tool breakage information can be communicated system wide so that a possible alternate machine center can be found (Kendall and Bayoumi, 1988). The interface of data among all operations are necessary for tool delivery and machine loading (Gaymon, 1986; Wick, 1987).

2.3.1.2 FMS and Individual Machine Control

At this level of FMS hierarchy, the individual machine is examined (Gray et al., 1989). A combination of tool characteristics (constraints) can be combined with overall system control. At issue is tool loading and placement within the tool magazine, work sequence, and tool replacement strategy.

The control of work flow is dependant on the loading of tools and job sequencing. Tang and Demardo (1988) examined a single machine with a limited tool magazine with known demand. The objective was to reduce the number of tool changes prior to the start of processing.

Vinod and Sabbagh (1986) also looked at tool allocation to the tool magazine. They considered an optimal allocation of spare tools. Because tool breakage is the largest factor that decreases productivity, spare tools will thus increase productivity. Vinod and Sabbagh proposed a closed queuing network optimization model which determines allocation of multiple types of tools to machines.

The number of spare tools also relates to another machine level issue, that of tool replacement. Replacement strategies that consider the variability of tool life and machining parameter are thought to be more realistic (Bao, 1980; LaCommere, Diega

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Diega, Nota, and Passabbabte, 1983). These models consider the option of changing several tools simultaneously. This differs from past tool replacement models which consider only a single tool and machine (Cook, 1966).

Sharit and Elhence (1989) explored a tool replacement strategy for an entire system rather than a single machine. This model did not seek an optimal solution, but rather, looked at the human and computer element of tool replacement. Sharit and Elhence attempted to trade off the economic loss of tool replacement with that of through-put time. Their tool replacement heuristic allows a tool to be replaced if its remaining life is less than the job processing time.

A recent study by Amoako-Gyampah, Meredith, and Raturi (1992) examined four alternative tooling allocation strategies. The first strategy used a bulk exchange of tools per period. For each period a machine is given all the necessary tools to process the jobs. This requires batching jobs according to the tools needed. At the end of each period, the machine gets a new set of tools. One assumption of this rule is that all tools have sufficient life. The second alternative tooling allocation strategy is referred to as tool migration. Tools are allowed to leave or enter a machine throughout the period. If a job requires a different tool, then it is sent to the machine. The third tooling allocation strategy is referred to as resident tooling. This principle is based on group technology methods. The rule attempts to form clusters of tool combinations at machines and permanently keep the tools at that location. The last tool allocation strategy used a combination of bulk exchange and resident tooling. Amoako-Gyampah et al. (1992) simulation results showed that rules one and four.

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four, which group tools so that job batching is possible, out perform the migration (rule two) and tool clustering (rule three) rules. Bulk exchange performed best in terms of both flow time and tardiness.

2.3.1.3 FMS and Tool System Management

Tool system management at the upper level of the control hierarchy, seeks to integrate the production planning system with tool control (Gray et al., 1989). Specifically, tool system management looks at tool inventory and scheduling.

Tool inventory is based on the number of tools and spares required. Zavanella, Maccarini, and Bugini (1990) examined different replacement strategies for tools with a stochastic life. The heuristic found to be most effective attempted to reduce the amount of wasted or unused life of replacement tools. The heuristic performs best with a limited tool supply and tool refurbishment delay.

Kouvelis (1991) sought to determine the optimal number of each tool type by developing a two-tier planning/allocating procedure. The long-term aspect focused on the optimal number of tools of each type and the short-term aspect attempted to minimize tool switches and to balance workloads.

Production planning in an FMS depends on tool capacity, which is affected by tool type and production part variety. Carrie and Perera (1986) explored how tool and product variety influences tool changes and tool ware. Tool changes occur for two reasons, tool wear and product variety. It was found that tool wear has a much greater effect on the number of tool changes than does product variety. For this reaso

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reason, tool life was a more limiting factor on capacity than is product variety. Thus, FMS planning should take tool life into consideration.

Other planning issues related to FMS involve grouping parts and tooling for effective production. Ventura, Chen, and Wu (1989) developed an algorithm for part grouping and tool requirements. By grouping parts that require similar tools, fewer tool changes are necessary, and larger batching of production is possible. The model also minimizes idle time, which helps reduce tool redundancy. Another model was developed by DeSouza and Bell (1991), who used a Rank Order Clustering (ROC) algorithm to group tools. The groupings are based on the job to be processed and required tooling. The cluster algorithm reduces the number of tool changes (setup) in the tool magazine. The model reduces the effort of managing and scheduling tools in an FMS environment.

2.3.2 Tools Scheduling in Non-FMS Machine Models

Although most tool scheduling models are set in a FMS environment, a number of other studies have focused specifically on tooling or incorporated it into their framework. One such model is the single-plant mold allocation which assigns molding tools to machines (Love and Vemuganti, 1978). The model attempts to satisfy production demands while having limited tool capacity and changeover restrictions. Tool capacity varies by period as new molding tools are added and old ones are reworked. The problem is formulated as a mixed integer program.

Another model which uses tooling as an element is by Brown et al. (1981).

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They looked at production and sales planning for multiple periods with limited shared tooling. In their model, forming tools (injection molds) were shared because they could produce a number of similar products with the same dies. Each tool was specific to a family of similar parts. Brown et al. formulated the problem as a mixed integer linear program, with tooling as a constraint on each periods production. The model determined how much of each product to produce and sell in each period.

Both Melnyk et al. (1989) and Ghosh et al. (1991) examined a single machine with tooling availability. In their first model, Melnyk et al. examined tool availability and its influence on shop performance. Tool availability is determined by the level of external demand (another machine) for each tool. A tool can remain at a machine for Y number of jobs. As Y decreases, tool availability decreases (tight tool capacity) and all measures of shop performance decrease. The implication is, the lower the tool capacity, the worse shop performance becomes. Another contribution from Melnyk et al. (1989) involves tool assignment rules, which were found to be more critical than job priority rules (dispatching). However, rules which consider both job priority and tool availability performed best. Rules that attempt to avoid tool changes (sequence dependent) perform poorly, except for tool change performance measures. If the rule considers a job's due date, its performance is improved. It should be noted that rules which attempt to avoid tool changes will vary in performance depending on the setup time constraints.

The level of sequence dependency was tested by Ghosh, et al. (1991) using the same model as Melnyk et al. (1989), except that various degrees of sequence depe

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dependency (severity of setup time between jobs) were added to the model. The effect of higher levels of sequence dependency (increased setup time) caused shop utilization to increase and shop performance to decrease. Other findings conformed to past work (Melnyk et al., 1989) which concluded that tool assignment rules are more important than dispatching rule decisions. The best performance was obtained when both tool condition and job priority was considered together.

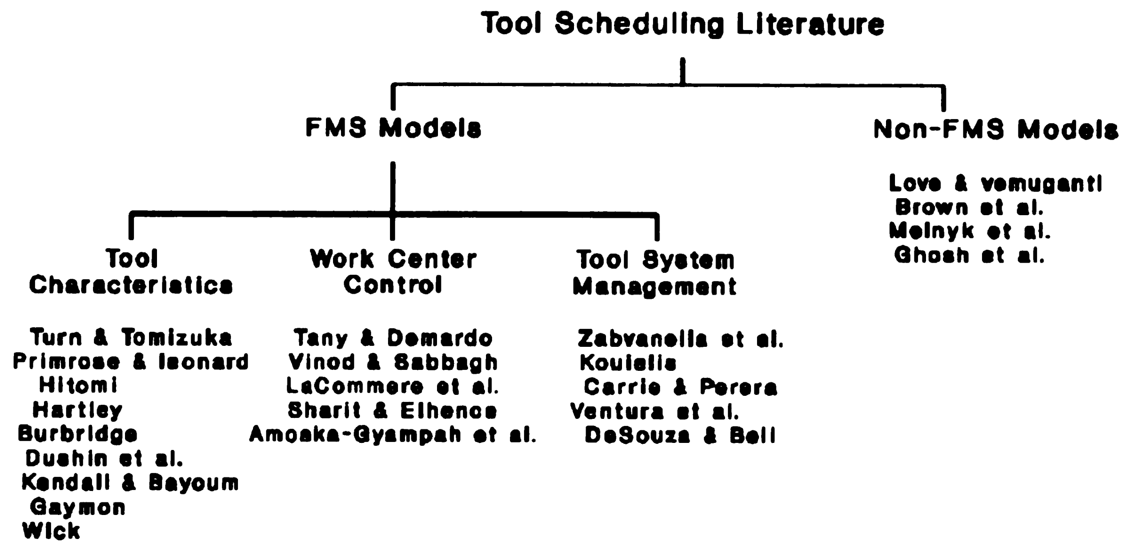
2.3.3 Summary of Tool Scheduling Literature

As Figure 2-3 shows, the literature on tool scheduling can be broken into: FMS and non-FMS environments. The majority of tool scheduling literature falls under the first group, FMS related. The reason for this is because of the high cost of tooling in FMS (Ayres, 1988). Gray et al. (1989, 1990) provide an in-depth review and categorization of the FMS literature. Gray et al. (1989) breaks decision making into a three level hierarchy from tool magazine size to tool placement/replacement decisions.

At the lowest level of the hierarchy there are a number of issues including: tool life, cutting economics, tool standardization, and data/information. The last issue, information, links and drives all three levels of the hierarchy. Information on tool and shop condition is passed to higher levels of planning.

The second level of Figure 2-2 hierarchy involves shop scheduling of work and tool allocation. Tang and Demardo (1988) looked at tool allocation with the objective of minimizing tool changes during processing. Amoako-Gyampah et al.

Figure 2-3 Tool Scheduling Taxonomy



(1992) considered four different tool allocation strategies and found bulk exchange to be the best performer.

At the top of the hierarchy is the planning of production and tooling. Ventura et al. (1989) developed a means of grouping jobs so as to reduce tool changes. Also considered at this level is the number of tools necessary for the system to meet demand (Kouvelis, 1991).

For non-FMS models of tool scheduling, articles by Melnyk et al (1989) and Ghosh et al. (1991) are the most relevant. Both look at tool control procedures simultaneously with dispatching rules. Other models by Brown et al. (1981) and Love and Vemuganti (1978) viewed tooling as a capacity issue and part of the production planning process.

2.4 MAINTENANCE

The objective of any maintenance program is to transform equipment (machines and tools) into a useful capacity. Machines and tools move through several conditions over time with the probability of failure varying at each stage. The final state for any equipment is failure. A maintenance program must consider the varying conditions of the equipment. Equipment maintenance can take place when one of two conditions exits: 1) pre-failure, or 2) post-failure. Pre-failure maintenance is usually referred to as preventive maintenance (PM). Post-failure maintenance is referred to as corrective maintenance (CM). Pre and Post failure are examples of two maintenance strategies, PM and CM.

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2.4.1 Maintenance Strategies

Maintenance strategies are usually grouped into two categories: 1) reduce the frequency of failure, and 2) reduce the severity of failure (Hardy and Krajewski, 1975; Krajewski and Ritzman, 1988). Preventive maintenance (PM) would be classified under the first category. Backup or equipment replacement would fall under the second category and is usually referred to as preparedness maintenance policy.

Gallimore and Panlesky (1988) defines five maintenance strategies: 1) Reactive, 2) Preventive, 3) Inspection, 4) Backup, and 5) Upgrade. A reactive maintenance strategy is identical to CM. Preventive and Inspection is usually grouped under PM. The difference is, preventive maintenance is based on a regular schedule while inspection maintenance is irregular and performed when the tools are being used. Backup is a maintenance strategy based on the availability of redundant equipment. Such an approach is justified when the cost of equipment breakdown exceeds the cost of having excess capacity. The last maintenance strategy involves the upgrade of equipment. With newer equipment, breakdown frequency diminishes, resulting in less costly maintenance.

2.4.2 Maintenance Models and Characteristics

2.4.2.1 Classification

A composite of breakdown and maintenance models can be found in a number of different articles (McCall, 1965; Pierskalla and Voelker, 1976; Sherif and

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Smith, 1981; and Lie at el., 1977). Breakdown is relevant because it often determines when maintenance activities take place. McCall (1965) conducted the initial survey which identified the assumptions and relationships found in various maintenance policies. This initial survey attempted to introduce the problem of scheduling maintenance when equipment experiences stochastic failure. Figure 2-4 provides a breakdown of McCall's various maintenance polices. McCall's (1965) two categories, known and unknown distribution of time to failure, describe different approaches to maintenance scheduling. The following is a description of the preventive or preparedness maintenance policies.

1). Periodic Policy: replace or inspect equipment at the time of failure or interval (age) N, which ever comes first.

2). Sequential Policy: next inspection interval is recalculated just after each maintenance action.

3). Opportunistic (multiple part - complex) Policy: when one of several component fails or interval N, which ever comes first. At that point in time all components are inspected. Each part has a stochastic life. All three of these policies, whether for preventive or preparedness, assume a known distribution for mean time to failure (MTTF).

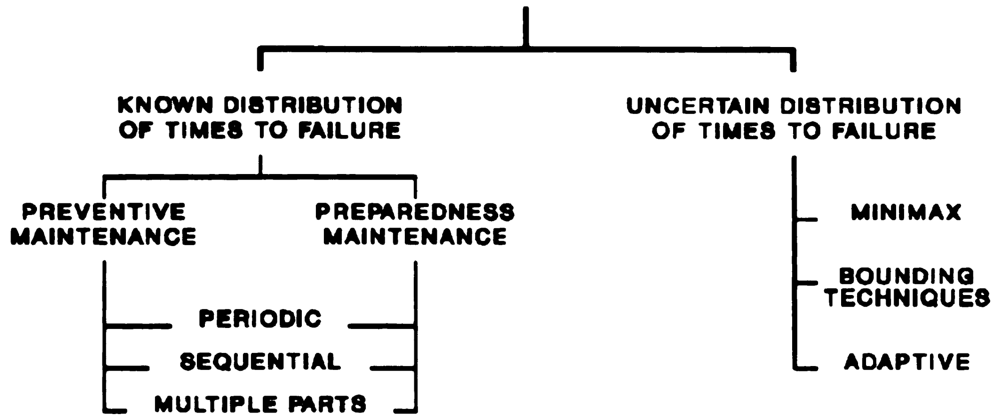
The following assumptions are utilized by all three models.

a. The system is either operating or has failed.

b. Failure is an absorbing state, partial operation is not possible.

c. Maintenance action renews the system immediately after completion.

Figure 2-4 Maintenance Policies
(McCall, 1965)



d. The interval between successive renewal points are independent random variables.

e. Maintenance costs or time penalty is higher if done after equipment failure rather than before.

Sherif and Smith (1981) provide information on which policy is optimal under various assumptions.

- For unlimited life systems, select the periodic policy.

- For systems with constant failure rates (exponential), maintain at failure.

- For systems with increasing failure rates (Weibull & Gamma), maintain a progressive schedule.

- For systems with a finite life, select the sequential policy.

- For complex multi-part systems, if:

1. Parts are independent: choose periodic or sequential scheduling for

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each part.

2. Parts are not independent: replace all parts when one fails.

McCall's second category develops maintenance policies when the distribution of time to failure is unknown. The following is a description of these three maintenance policies.

1) Minimax: minimizes the maximum maintenance losses, whether it is costs, downtime, or both. Nothing is known about a system's failure distribution. The optimal policy is to maintain at failure.

2) Bounded: partial information on the distribution is known (failure rate). Chedyshev-type bounds are applied to one of the models previously discussed.

3) Adaptive: if subjective information exists about failure distribution, then the Bayesian adaptive techniques are used.

Based on available information, either preventive or preparedness policies would be selected and modified using one of the three techniques mentioned above.

Pierskalla and Voelker (1976) extended McCall's work and adds maintenance policy classification as either a discrete or continuous system review. Most of McCall's classification would fall under the discrete time model. Pierskalla and Voelker (1976) separated the continuous time model, which attempts to minimize costs, into three areas which are presented below.

1) Age dependent: this is a modification of the periodic and sequential maintenance polices which consider critical threshold costs. Once beyond this cost, it is advantageous to replace the equipment.

2) Shock: this model assumes that failure occurs due to an external shock to the equipment. External shock occurs based on a Poisson process and have an accumulative effect.

3) Interacting Repair: this is another opportunistic policy which includes cannibalization, multistage replacement, and variable repair rates. Cannibalization attempts to maintain equipment based on parts from an identical unit. The objective is to provide the best possible configuration for operating equipment given no spare parts (units).

Multistage replacement differs from cannibalization in that a new part is always available. The objective with multistage replacement is to place the spare part where it yields maximum benefit. This tends to be where failure costs are highest.

Variable repair rates add the element of maintenance capacity as a decision variable. Maintenance capacity is usually expressed as a service rate (that is, the number of workers performing the service). The objective is to find a service rate which minimizes the long run costs.

Sherif and Smith (1981) also discuss deterministic maintenance models and assumptions. Under deterministic models, equipment life is known with certainty. The optimal maintenance policy is periodic with equal length maintenance actions. This is based on the following assumptions.

a. Outcomes of maintenance are non-random.

b. Maintenance restores the system to original condition.

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c. Failure is observable and instantaneous.

d. Identical parts have the same known time to failure.

2.4.2.2 Failure and Service Time Distributions

Most models that have examined the two components of maintenance, time to failure and service time, have modelled the time duration as a stochastic process (Lie et al., 1977,; and Sherif and Smith, 1981). Several different types of distributions have been used to model failure time (MTTF) including: exponential, Erlang, Weibull, Gamma, Rayleigh, normal, log-normal, uniform, extreme value, and general. Negative exponential is the most commonly employed distribution because of it's constant failure rate. While mathematically easier to use, data collected from industry support the exponential application (Lie, et al., 1977). The use of normal distribution is justified based on data from the aircraft parts industry. When the failure distribution is skewed, the gamma family is a better choice. For systems characterized by fatigue failure, like tooling, the Weibull distribution is suitable. Log-normal is not considered a good choice for mean time to failure, but rather, fits better as a repair time distribution.

Distributions used to model maintenance renewal time also cover the same group as mean time to failure: exponential, Erlang, Weibull, gamma, Rayleigh, normal, uniform, and general (Lie et al., 1977). The preferred distribution is log-normal. Exponential is considered a good choice when there is a high frequency of short repairs with a few long repairs. If repairs (renewal) of each item takes an equal length of time, then uniform distribution is an appropriate choice.

A few articles use unique distribution to model failure (Sherif and Smith, 1981). One of the few research articles which addresses the issue of tool failure and maintenance is by Vanderhenst, Van Steelandt, and Gelders (1981). The objective was to minimize tool down time. The tool life or time to failure used in this model was based on historical data which resembled an exponential distribution.

Denzler et al. (1987) modeled an FMS with breakdown uncertainty by using a deterministic approach. Breakdowns are classified as either major or minor. Major breakdowns occur once every ten shifts and require ten hours to perform the maintenance. Minor breakdowns occur once every two shifts for a maintenance duration of two hours. Deterministic distribution simplifies the model but tends to over estimate the benefits of scheduling policies.

2.4.2.3 Maintenance and Tool Availability

The frequency of tool failure and the length of time it takes to repair the tool, determines the tool's availability. It should be evident that tool availability determines system performance. Lie et al. (1977) classifies availability into three (Markovian) categories: 1) instantaneous, 2) average uptime, and 3) steady-state. Each of these three categories look at a different time intervals when estimating availability. Another means of determining availability is with a ratio of uptime to total possible time, which can be measured directly or estimated using the expected value function (Goldman and Slattery, 1964). Two other methods of expressing availability is with inherent availability:

$$A_i = \frac{MTBF}{MTBF + MTTR}$$

where: MTBT = mean time between failure

MTTR = mean time to repair

and achieved availability;

$$A_a = \frac{MTBM}{MTBM + M}$$

where: MTBM = mean time between maintenance

M = mean maintenance time of both CM and PM

The importance of the availability measure stems from the fact that it gives a means of evaluating or comparing system performance. When different distributions are used to test systems performance, the same expected value for availability allows for a more accurate comparison.

2.4.3 Corrective and Preventive Maintenance Scheduling

2.4.3.1 Descriptive Models

There are a number of different models that provide a means of implementing and controlling a maintenance program. Bojanowski (1984) used the Materials Requirements Planning (MRP) logic to develop Service Requirements

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Planning (SRP). SRP attempts to establish routine equipment inspections and monitors wear to prevent machine failure and improve shop performance. By time phasing maintenance inspections, plans for repair labor and materials can be determined. Bojanowski (1984) estimates that 70 percent of machine failure is due to either the lack of awareness of a need for service, or lack of proper service inspection interval. Bojanowski also stated that equipment failure is especially common for high wear parts like forming tools.

A maintenance model proposed by Newman (1985) also used MRP logic. He states that by using a periodic planned inspection, the preventive maintenance program could reduce the risk of machine failure. Newman (1985) goes farther than Bojanowski (1984) by adding a master maintenance schedule to the preventive maintenance requirements planning (PMRP). The master maintenance schedule determines when a service activity needs to occur. For example, service is performed after X number of products are produced, after a certain number of operating hours, or when mean time between failure is reached. By selecting one of these values, the point at which to preform preventive maintenance is determined.

A recent article by Maggard and Rhyne (1992) presents an integrated model of maintenance. Total productive maintenance is an attempt to integrate all functions with maintenance, especially production. The benefits obtained with this approach resulted in a 6 percent increase in machine availability.

A case study by Christer and Whitelaw (1983) examined the benefits and requirements of a maintenance program. They point to the critical need for historical data and the ability to collect data continuously. Information on the causes and consequences of machine failure helps prevent future failures. A maintenance program should not only help eliminate failures, but provide an appropriate PM schedule. Christer and Whitelaw's estimate that breakdowns account for up to 20 percent of lost production time.

A subsequent article by Christer and Waller (1984) examined PM applied to a vehicle fleet, in particular the timing and frequency of PM. A unique feature of this model is the concept of delayed PM. If a vehicle breaks down, the part that failed will be repaired, but should other parts that show wear be replaced at the same time (a form of PM)? If not repaired, should the vehicle be rescheduled for PM? Christer and Waller research showed the complicated issues involved in maintenance when multiple parts are present which may be interrelated. Their model demonstrates that PM must be tailored to each situation.

2.4.3.2 Analytical Models

Vanderhenst et al. (1981) explored PM and CM strategies for tools. If preventive maintenance takes place when ever a changeover or tool change occurs, then little or no production time is lost because of these conditions. If, however, a tool or machine should fail, then unplanned maintenance take places and system availability decreases. It is estimated that availability loss due to breakdown is 8 percent. Depending on the penalties for CM, Vanderhenst etal. (1981) explored the trade offs between tools during changeover (setup) and tool changes due to tool failure.

Kay (1978) examined whether PM is more effective than CM. The time to system failure is modeled with a Weibull distribution (where parameter b is $1 < b < 2.5$). The objective is to optimize the percentage decrease in maintenance costs. It is found that optimal cost performance does not equate to maximum availability, which is contrary to many other studies. In addition, when its cost is lower PM is preferred over CM because availability is greater. The benefits associated with PM or CM depend on the values given to both costs and availability.

Banerjee and Burton (1990) simulated a job shop and examined a number of different maintenance strategies and maintenance capacity issues. Maintenance capacity is determined by the number of workers and maintenance allocation rules (6 rules). Corrective maintenance is always given priority over preventive maintenance. As for PM, the five rules are: (1) No PM performed, (2) PM every .3 periods of operation, (3) PM every .5 periods of operations, (4) PM every 1 period of operation, and (5) PM every 1.5 periods of operation. Mean time between failure was modeled using an Erlang-4 distributions (MTBF mean varied from 70 to 130 hours). CM repair time was modeled with an exponential distribution (mean from 2 to 8 hours) and for PM repair time a uniform distribution was used (average time from 1 to 4 hours). The findings show, that as the frequency of PM increases, the average PM delay decreases, and flow time increases. In addition, as shop utilization increases, the maintenance scheduling method used takes on greater importance.

This is logical, since down-time is more detrimental to shop performance.

2.4.4 Production and Maintenance Scheduling

Few articles have considered the implications of maintenance actions on, or in the presences of production schedules. Ram and Olumolade (1987) developed maintenance schedules that consider the production plan, and a total expected costs formulation that considers capacity per period, given the probability (Weibull distribution) of machine failure. The model also included the average maintenance time for PM and CM. The objective was to minimize the costs of PM and CM on a per period bases. The model does not find an optimal cost, but simply a means of evaluating the cost tradeoffs between CM and PM.

Pate-Cornell, Lee, and Tagaras (1987) developed combined maintenance and production rules. The maintenance policy includes: no PM, scheduled maintenance, and maintenance on demand during inspections. The latter policy is performed using the production inspection process. If inspection indicates a need for maintenance, (poor product quality) then maintenance is performed. This policy works well when the shop is stable. In an unstable environment, the scheduled maintenance policy works best. Planned maintenance allows the system to adjust production around maintenance and machine availability.

An FMS model with machine failure was developed by Denzler Boa, and Duplaga (1987), to determine the effect of machine failure on system performance. Machine breakdown is classified as either minor or major, which is associated with maintenance severity. Breakdowns do affect performance in a FMS, but short term production scheduling procedures can lessen the impact of the breakdown.

Hsu (1992) examined how PM influences a production system and showed that the optimal maintenance policy is very sensitive to the system's monitoring technology. Monitoring technology includes vision systems and torque sensing equipment. Should such systems exists in the shop, it is optimal to perform maintenance only when the monitoring equipment so indicates. If such monitoring systems do not exist, then the model found that planned PM can improve system performance.

The effect of maintenance on production was also analyzed by Wacker (1987). Wacker looked at the elements of production throughput time of which down-time is a component. He proposed that a truly effective PM program would not add to a systems throughput time because it would be performed during setup. For zero inventory (Hall, 1983) and JIT systems, such an approach is advocated, but in reality the system is not likely to be this efficient. Variation in duration and frequency of PM can also add to throughput time. Unscheduled maintenance, whether CM or PM, will cause queues to increase and an increase in throughput time. The objective of PM in reducing throughput time is to decrease unplanned maintenance (CM) while not causing undue delays in production startup after a setup change.

Finally, Ghosh and Gaimon (1989) considered as part of their model the effect of various levels of PM on capacity. They found that PM can slow the deterioration of machines, which can alleviate bottlenecks, and that higher levels of PM can provide higher levels of capacity.

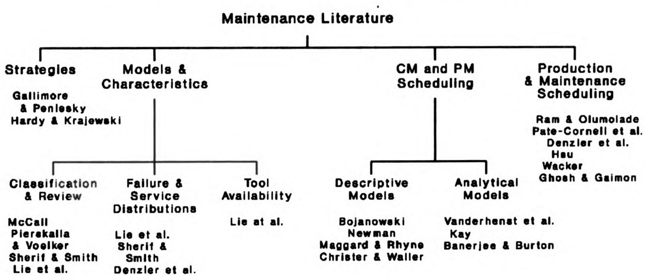
2.4.5 Summary of the Maintenance Literature

Figure 2-5 provides a breakdown of the literature reviewed in this section. The figure does not show that maintenance tends to be categorized as either preventive (PM) or corrective (CM). Maintenance can be further broken down in an attempt to either reduce frequency or severity (Hardy and Krajewski, 1975). Further refinement of maintenance strategies can be found in Gallimore and Penlesky (1988). While these articles are descriptive, more analytical models were described by McCall (1965), whose maintenance scheduling approaches were outlined in Figure 2-4.

Failure and service time have been modeled in a variety of ways. Lee et al. (1977) and Sherif and Smith (1981) describe many of the approaches used in distributions. The most common stochastic distributions used for failure and service include: exponential, Erlang, Weibull, gamma, normal, log-normal, and uniform. Stochastic distributions are particularly relevant to tool availability. Methods of calculating availability is based on mean time to failure and expected service time.

The scheduling of production and maintenance is presented using both descriptive and analytical models. In the descriptive model, Bojanowski (1984) and Newman (1985) used MRP logic in the planning of maintenance. For the analytical models, a number of different PM procedures were examined and compared to CM

Figure 2-5 Maintenance Taxonomy



(Vanderhenst et al., 1981; Banerjee and Burton, 1990). The research found that when the cost of PM was lower than CM, PM improved performance. Excessive or frequent PM can also cause tool availability and shop performance to decrease.

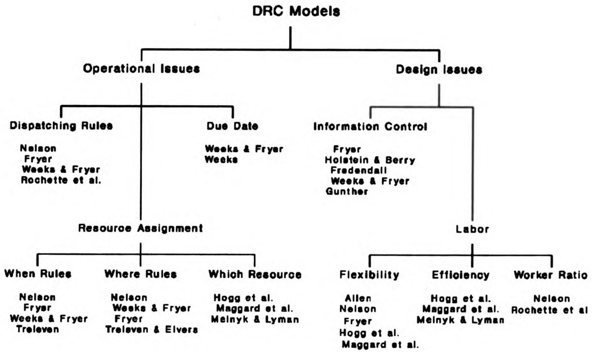
2.5 DUAL RESOURCE CONSTRAINT AND LABOR SCHEDULING MODELS

A DRC shop involves more than just a machine limited shop environment. The DRC shop has two limited resources which must both be available before processing of work can start. The simultaneous availability of two resources differentiates this research from the single constraint machine limited studies which dominates the literature. Review articles by Blackstone, Phillip, and Hogg (1982), Day and Hottenstein (1970), Graves (1981), and Panwalker and Iskander (1977), provide an excellent background on machine-limited research. Only Blackstone et al. and Day and Hottenstein briefly discuss the DRC research. Treleven (1989) was the first to provide a detailed review of past research in DRC articles.

In the DRC field, a number of issues have received attention, as indicated in Figure 2-6. Treleven's classification of the various DRC models will be applied in this literature review. The two major issues which have been addressed are operation and design.

It should be noted that most DRC models look at machine and labor as the constraining resources. Melnyk et al. (1989) and Ghosh et al. (1991) are the exceptions and consider tooling as yet another limiting resource. Hogg, Phillip,

Figure 2-6 Taxonomy of DRC Research



Maggard, and Lesso (1975a, 1975b) discuss the possibility that tooling can be a constraint, but they do not directly address any tooling issues. Instead, what Hogg et al. developed was a multiple constraint model which allows for a third constraint like tooling.

2.5.1 Operational Issues in DRC

Operational issues in DRC models look at control procedures such as dispatching rules, due date assignment, and labor allocation. These procedures are enacted while the model is in operation. They determine how and when decisions in the DRC model function. Operational issues are dynamic in that procedures are enacted when certain conditions are present in the model. What separates the DRC models from the machine-limited research is that while both are concerned with dispatching and due date rules, the DRC model must also decide on labor allocation.

2.5.1.1 Dispatching Rules

Early DRC models examined various dispatching rules to see how multiple resources alter performance. LeGrande (1966), Nelson (1967, 1970), Fryer (1973), Rochette and Sadowski (1976), and Weeks and Fryer (1976, 1977) found that dispatching rules had a significant affect on shop performance. Nelson found that the shortest operating time gave the best results in terms of mean flow time, while the first in system was better with respect to variance of flow time.

Weeks and Fryer (1976, 1977) found that the relative performance of various dispatching rules depends on the tightness of the due date procedure. When first come first served (FCFS), shortest processing time (SPT), and least slack per remaining operations (SOPN) were tested with tight due dates, SPT was the better shop performer. As due dates were loosened and limited labor transfers, SOPN became the best performer.

LaGrande (1966) and Bulkin, Cooley, and Steinhoff (1966) used actual data in a simulation to determine whether dispatching rules have a major influence on performance. SPT (MINPRT) was ranked first, minimum slack (MINSOP) ranked second, which is consistent with Nelson (1966). The ranking was based on an average of ten performance measures. When the weight of the ten performance measure were adjusted to favor early job completion, MINSOP became the best performer. Bulkin et al. (1966) applied the MINSOP dispatching rule to an actual operation, orders completed on time rose 10 percent, and both machine and labor utilization increased.

2.5.1.2 Due Date Rules

Most DRC models assign due dates based on the total work content rule (TWK) described by Conway et al. (1967). As stated previously, Weeks and Fryer (1976) examined both dispatching rules and due date assignments. They found that the due date assignment procedure (TWK) has a significant effect on shop performance. Due date has the greatest influence on the lateness performance measures. The tightness of the due date assignment has a more important effect on shop performance than do dispatching rules. A subsequent study by Weeks and Fryer (1977) examined the effect of the K value used in the Total Work Content (TWK) due date assignment rule. The objective was to determine the minimum cost due date multiplier (K) value that enhanced shop performance. They found that the value selected for K (in TWK) was dependent on cost structure, dispatching method, and labor assignment rules.

Weeks (1979) further analyzed due date assignment rules in relation to shop conditions. Seven different rules were tested, three of which used TWK with different K values. Those rules that include information on shop congestion or job flow time provided more predictable due dates than previously tested TWK methods. In addition, it was found that dispatching rules which incorporate due dates (least slack) perform better than process oriented rules (SPT).

2.5.1.3 Labor Assignment

Labor assignment is a major factor in all the DRC models. The two most important issues are *when* and *where* labor is assigned. Other relevant issues are; which worker to select and whether the labor decision is centralized for decentralized. The latter issues will be addressed under information control.

The decision about *when* to transfer workers has been shown to be a more important labor assignment issue than *where* to send the worker. The *when* decision determines the eligibility of the worker to be transferred. Nelson (1966, 1970) examined the effect of cross training and the *when* labor transfer. He found that the level of cross training, or the ability to move between machines, has a major influence on shop performance, as does the *when* labor assignment. The decision of *when* to move a worker was based on shop and cross training information.

Fryer (1973, 1974a, 1974b, 1976) and Weeks and Fryer (1976) showed that the *when* rule had a significant effect on shop performance. Fryer (1973) found that *when* rules, both intra and inter-divisional, were more important than *where* labor rules. Fryer also concluded that the *when* labor rule was more influential on shop performance than the dispatching rules. From the various studies by Fryer, it was determined that "when idle" (all jobs in queue are done) labor transfer rules were consistently better performers.

Treleven (1987) did a more complete comparison of *when* labor rules by examining: when idle (QUE), when the current job is done (JOB), and when to pull worker (PULL). The last rule, an attempt to allocate a worker to areas of need, is a combination of *where* and *when* to relocate workers. The PULL labor rule outperformed the other two *when* rules.

The fact that Treleven's (1987) PULL labor rule combines issues of *when* and *where* to send workers presents a paradox in the literature. Nelson (1967) proposed that *where* labor rules could improve mean and variance of flow time. Studies by Fryer (1973), Weeks and Fryer (1976), and Treleven and Elvers (1985) showed that *where* rules had little effect on shop performance. Treleven and Elvers examined several *where* rules and found that they had no significant effect, except on the number of labor transfers. Holstein and Berry (1972) found that the *where* labor rule did have an impact on shop performance. The *where* rule reduced the number of transfers without greatly increasing flow time. Where to send workers is based on the longest queue in the shop. Holstein and Berry's *where* rule is similar to Treleven's (1987) PULL rule which seeks to combine *when* and *where* labor rules. Melnyk and Lyman (1991) supported this approach by showing how varying labor efficiency at work centers makes the decision about *where* to allocate labor more important than has been recognized in past research.

The last labor selection issue addressed here is which resource (worker) to select from. This assumes that more then one worker is idle and that the selection is made from those available. If the labor resource is homogeneous, then selection is not an issue. If the labor pool is heterogeneous, then the selection takes on importance. Hogg, Phillips, and Maggard (1977) found homogeneous work-forces to be superior to heterogeneous ones. In most cases, it is neither practical nor possible to have workers or other resources which are equally efficient.

Maggard, Lesso, Hogg, and Phillips (1973, 1976), Maggard, Lesso, Keating, and Wexler (1974), and Hogg, Phillips, et al. (1977) modeled labor with varying efficiency. One goal of this research was to illustrate labor blocking which occurs only when resource efficiency varies. This occurs when less efficient resources are allocated to perform work and more efficient resources are prevented or blocked from performing the work. If labor blocking can be prevented, flow and queue times can be reduced. As the variation in labor efficiency increases, shop performance deteriorates. The key to shop performance depends on the availability of efficient labor, a conclusion also supported by Melnyk and Lyman (1991).

2.5.2 Design Issues in DRC

Design issues, like labor flexibility, efficiency, worker to machine ratio, and information control deal with static aspects of the model. Design issues set the parameters in which the operational issues must contend and, thus, can have a direct bearing on operations.

2.5.2.1 Labor

Design issues related to labor have three components: flexibility (cross training), efficiency, and machine-staffing levels. These components are interrelated, for example, the degree of flexibility or cross training can influence the ratio of workers to machines. Allen (1963) was the first to demonstrate the benefits of worker cross training. He claimed workers who were cross trained could be used more efficiently because workers can be allocated where needed. Nelson (1967) and Fryer (1974) showed that as the level of cross training increases, the machine-staffing levels can be reduced without decreasing performance.

Nelson (1967, 1968), Fryer (1973, 1976), Hogg et al. (1977), and Park and Bobrowski (1989) found that with increased levels of labor flexibility, shop performance increased. The benefits of greater flexibility can be achieved with a small addition in cross training. Beyond a certain point, the benefits of cross training on shop performance is only slight.

With regard to efficiency and flexibility, Nelson (1968) demonstrated that as the variability of labor efficiency increases, so does the need for additional flexibility. This was supported by Hogg et al. (1977) and Maggard et al. (1980). Hogg et al. developed three different models: varying efficiency by worker (LD), varying efficiency of worker by machine (MCD), and varying efficiency of worker by both machine and worker (L&MCD). L&MCD represents the greatest variance in efficiency; because of this, labor allocation rules based on the most efficiency take on greater importance.

Whether the workforce is homogeneous or heterogenous, the level of cross training affects the machine-staffing requirements. Maggrad et al. (1973), Hogg et al. (1975), Fryer (1975), Weeks (1979), Elvers and Treleven (1985), and Treleven and Elvers (1985) all analyzed the effect of staffing levels. In general, they conclude that the best shop performance for machine-staffing levels is obtained with a worker to machine ratio of between 1:2 to 2:3. When staffing levels exceed the 2:3 ratio, worker idleness increases dramatically. At staffing levels less than 1:2, resource utilization is at their maximum which causes shop congestion and deteriorates performance.

2.5.2.2 Information Control

Control of information as part of the design determines where a decision is made or how it affects the decision process. For example, the decision to move a worker can be either centralized or decentralized. Gunther's (1979, 1981) work on transfer delays revealed that as the delay of moving a worker between machines increases, shop performance (mean and variance of flow time) deteriorates for traditional labor assignment rules. A parametric rule which considers transfer delay information cause worker transfers to be delayed and keeps shop performance from deteriorating.

Another example of information control is found in Fredendall (1991), whose DRC model used an order review/release (ORR) method to control work on the shop floor. ORR releases work based on various types of information, such as shop load. The study revealed that how information is used is more important than what information is used. It was also found that by using ORR, both dispatching and labor assignment were not as significant as indicated in past research.

When looking at the control of labor assignments, centralized verse decentralized information determines the degree of flexibility. Nelson (1967) found that as control of labor transfer becomes more centralized, mean and variance of flow time decreases because information regarding the entire shop is used. With decentralized control, information regarding transfers are localized on divisional levels and do not consider the needs of the entire operation. Fryer (1974a, 1974b, 1976) reached similar conclusions when he examined the *when* and *where* labor assignment rules.

2.5.3 Summary of the DRC Literature

The DRC literature, generally centers on labor allocation and enhancing shop performance. The labor allocation issues focus on *when* and *where* to send workers. Most studies showed that *when* to move a worker was more important than *where* to send the worker (Treleven, 1989). Two basic rules about *when* are: when idle, and when the current job is done. A third rule, PULL, which was developed by Treleven (1987), was also found to be effective. PULL is a combination of the *when* and *where* decisions. As for *where* to send workers, the rule most commonly used is the longest queue. A third issue of labor allocation deals with varied labor efficiency (Nelson, 1967; Hogg et al., 1977). When worker efficiency varies, selection of either a capable or most efficient worker becomes relevant.

Another major focus in the DRC research looks at shop performance through dispatching and due date tightness. Both dispatching and due date tightness were found to have a significant effect on performance (Weeks and Fryer, 1976, Weeks, 1979).

2.6 SEQUENCE DEPENDENT MODELS

Sequence dependency involves examining the relationship between jobs. Every job requires certain unique resources at each step in its processing. In the context of this research, the unique resource is the combination of machine and tooling. The relationship between jobs on a particular machine involves which tooling resides currently on the machine. Sequence dependent rules examine the tooling attribute (or other attributes) of jobs to find those requiring the same tooling resource and to set their priority ahead of other jobs. The objective behind sequence dependency is to schedule jobs based on the current tooling setup or commonly required resources.

It should be noted that sequence dependent scheduling rules and group scheduling rules are different (Wemmerlov, 1992). Group scheduling attempts to avoid setups by grouping jobs into families that require similar tooling setups. Sequence dependent scheduling rules are myopic in that they examine the current setup and changeover time. Both, however, consider the interrelationship of jobs in queue.

2.6.1 Sequence Dependent Scheduling Rules

While the benefits of sequence dependent scheduling are apparent, there is limited research which examines this environment. Gavett (1965) conducted some of the earliest research in this area. He looked at selecting the next job based on the current setup which requires minimum setup time. The objective was to minimize facility downtime (or setup time) over a finite number of jobs. Using deterministic, uniform, and normally distributed setup time, Gavett showed that such a selection procedure performed better than a random job selection rule, although the benefits depended on the variability of both setup time and batch size.

A study by Hollier (1968) also selected jobs on the basis of current setup. Hollier compared his current setup dispatching rule to several common dispatching rules (FCFS, SPT, EDD, etc.). With normally distributed setup times, the model found that rules which considered current setup performed better on several measures, such as machine idle time and job lateness.

Wilbrecht and Prescott (1969) examined dispatching rules that do and do not consider sequence dependency. Prioritization based on similar setups (SIMSET) performed significantly better overall than did other dispatching rules. Although SIMSET did best in only three out of the nine performance measures, its overall consistency allows it to be the best overall rule.

2.6.1.1 Tooling Sequence Dependency

Sequence dependency is usually a function of the tooling on a machine and not the machine itself. The machines ability to process, is a function of the tooling on a machine. This point was made in the discussion on FMS. An FMS tool magazine determines what jobs can be processed through the work center. For this reason, attention is focused on determining the optimal magazine load. For less automated machining systems, like stamping and molding, tool loading is not an issue but tool changeover (setup) is. White and Wilson (1977) discussed how cutting tools have various levels of sequence dependency. The levels reflect the degree of setup changes necessary which may include tool changes, fixture changes, and machine modifications such as speed. White and Wilson collected actual data on setup changes to develop an equation for setup time predictions. The data shows how sequence dependent scheduling can reduce setup time.

Daoud and Purcheck (1981) examined how reducing the number of tool changes via sequence dependent scheduling can improve shop performance. They found that sequence dependent scheduling increases machine utilization and timely job completion rates. They used a traveling salesman matrix to assign jobs on the basis of lowest change-over costs. An assumption is that a job is tool specific, not machine specific, and thus can be processed on any machine which reduces change-over costs. While this model is useful in the planning process, it does not consider resource availability or loading. The models objective is to reduce setup time without considering other issues.

Melnyk et al.(1989) and Ghosh et al.(1991) developed two models which looked at tool sequence dependency and resource availability. Melnyk et al. looked at tool control rules combined with dispatching rules that attempted to avoid setup changes. One rule attempted to avoid a setup change, while the other incorporated due date priority. These sequence dependent rules reduced the number of setups as compared to traditional dispatching rules. The sequence dependent tool rule which considered due date priority, also performed well in terms of a job tardiness and flow time (depending on the dispatching rule used).

Ghosh et al. (1991) modified the model to look at the impact of sequence dependency. The degree of sequence dependency was based on different percentages of setup time to processing time. The higher the percentage, the longer the time for setup. As the severity of setup time increased, the number of tool changes decreased, and the extent of sequence dependency increased.

2.6.2 Group Scheduling

Group scheduling categorizes jobs according to common attributes. In this case, the attribute is common setups (major setup changes) with the possibility of small changes (minor setup changes). This is an important feature in determining how cellular manufacturing is obtained. While group scheduling has been applied to cellular manufacturing, group scheduling is also applicable to other environments. Hitomi and Ham (1977) showed that a flow pattern environment with group scheduling has a significant effect on shop performance. Their results showed that rules that seek to reduce setup through job sequencing do improve performance. As the ratio of setup to processing time increases, so do the benefits of sequence dependency.

Baker and Dzielinski (1960) examined a single machine with sequence dependent family rules. At issue was whether family-oriented rules perform better than process oriented rules (SPT). The family rules analyzed in this study were based on an exhaustive procedure which processed all jobs within a family before changing. Baker and Dzielinski were also interested in the selection process of the next family. Their research showed that rotating among the families of jobs was superior to choosing the next family by minimum setup time. Furthermore, they concluded, that at high levels of shop congestion, family (group) rules work better for flow time measures.

Sawicki (1973) compared Baker's (1960) exhaustive family rules to rules that allow truncation. Truncation of the current family setup takes place when a certain amount of processing time has elapsed. The objective was to improve due date performance. This type of truncation process would be applicable to environments where a resource has a finite life, such as tooling. Sawicki determined that exhaustive family rules are more efficient in machine utilization and flow time, but are only slightly better on due date issues.

Three scheduling rules were developed and tested by Mosier, Elvers, and Kelly (1984) that looked at different information in group selection. The three rules were: highest average job priority (AVE), highest work content per family (WORK), and economic benefit of changing setup (ECON). ECON differs from the other two rules in that it allows switching between families. Results showed that group scheduling rules perform better on flow time and mean lateness than do regular dispatching rules. Overall, WORK was the best performer, but ECON was a close second.

Whereas, Mosier et al. looked at group selection based on the combined characteristics of the group, Mahmoodi, Dooley, and Starr (1990) and Mahmoodi, Tierney, and Mosier (1992) tested group selection based on a single job's attribute within the group. The single attribute was based on a priority determined by the dispatching rule. The rules tested include: first come first served of all families (FCFAM), earliest due date from all families (DDFAM), and minimize number of setups from all families (MSFAM). MSFAM attempts to utilize sequence dependency by selecting the next family which requires the least setup time change. A comparison of family rules showed that FCFAM was the worst rule, while

DDFAM was best overall. MSFAM showed excellent performance on average flow time because it attempted to avoid setup changes more than the other rules. This also explains why MSFAM was such a poor performer on average tardiness.

The previous group/family selection rules tend to be exhaustive because they process all jobs within a family before changing setup. The problem is, such rules ignore other job priorities which may be higher. Mahmoodi and Dooley (1991) examined this issue by comparing exhaustive versus non-exhaustive family scheduling heuristics. They compared the exhaustive rules (DDFAM and MSFAM) to two non-exhaustive rules (SLFAM and DKFAM). SLFAM processes all job within a family until another family has a job with negative slack, at which time the setup is changed to the new family. DKFAM processes the current family until the due date of the first job in the current family reaches C (a constant that is empirically determined) time units greater than the next most critical job in another family. As compared to exhaustive rules, both DKFAM and SLFAM attempt to reduce tardiness. Results show that MSFAM still performs best with respect to mean flow time and proportion of tardiness. DKFAM was best in terms of mean tardiness but worse with respect to proportion of tardiness. MSFAM and SLFAM were poor performers regarding mean tardiness. Mahmoodi and Dooley concluded that exhaustive rules are preferable to non-exhaustive rules in most cases.

Another issue known to influence the affect of group scheduling or sequence dependency include shop conditions and the ratio of setup to processing time. Ruben et al. (1991) showed that as shop utilization increases, so do the benefits of group scheduling. This also held true when the ratio of setup to processing time increased. Wemmerlov (1992) showed that as the number of groups diminish, so do the number of setups with the result being lower mean flow time. Wemmerlov also showed that when demand patterns are skewed toward one family, setup time is reduced, resulting in lower flow times.

2.6.3 Summary of the Sequence Dependency Literature

Regardless of whether sequence dependency or group (family) scheduling terminology is used, the objective is to reduce the frequency of setup changes. By reducing the number of setup changes, shop performance is enhanced (Baker, 1984b; Mahmoodi et al., 1990). The current machine setup is compared to the queue to find the next job which minimizes the setup change. Gavett (1965) and Mahmoodi et al. (1990) found that this method of selecting the next family of jobs result in better shop performance.

The difference between sequence dependent rules and group scheduling lies in how the queue is examined. Group scheduling selects the next group (family) based on a family characteristics or within group job attribute. If group selection is based on a job attribute within the group such as processing time or least slack, then the dispatching rules for job selection should be based on the same attribute for the best results (Mahmoodi et al., 1990). One assumption of group scheduling involves major and minor setups (Mosier et al., 1984; Mahmoodi et al., 1990; Mahmoodi and Dooley, 1991). Major setup time is incurred between groups, while minor setup within groups is incurred (and often is ignored). In contrast, sequence dependency does not distinguish between these two types of setups, but simply models it as a deterministic or stochastic distribution.

The issue of whether to use sequence dependency or group scheduling is an important issue in tooling control. Tool setup changes have been modeled as sequence dependent, and not as group scheduling (White and Wilson, 1977; Ghosh et al., 1991). To date, no research has examined tool control and group scheduling techniques together.

2.7 SUMMARY OF LITERATURE REVIEW

While there is extensive body of literature in a number of areas related to this research, no work has specifically looked at production scheduling and tool control. The model developed for this research is a result of past research and includes some of the following variables:

- Tool life distributions,
- Maintenance service time,
- Maintenance policies (CM vs. PM)
- Frequency of Maintenance,
- Tool allocation/scheduling,
- Tool sequence dependency rules.

While the literature provides a foundation from which this research was derived, it also points out gaps that exist. The following are some of the gaps that exist.

- No research in DRC schedules limited resources other than labor.

- DRC research which examines scheduling has not addressed the issue of finite life resources or maintenance.

- There is a lack of specific shop scheduling procedures for both production and maintenance.

- Sequence dependencies effectiveness, has not been analyzed in the presences of tool failure or scheduling maintenance.

By examining these gaps in the research, a better understanding of shop floor control is possible. Managers of production shops face many of these problems daily and must resolve them by any means. The intent of this research is to provide insight into the problems managers face and suggest methods to resolve them.

CHAPTER 3

TOOL PLANNING AND CONTROL: A CONCEPTUAL FRAMEWORK

3.1 INTRODUCTION

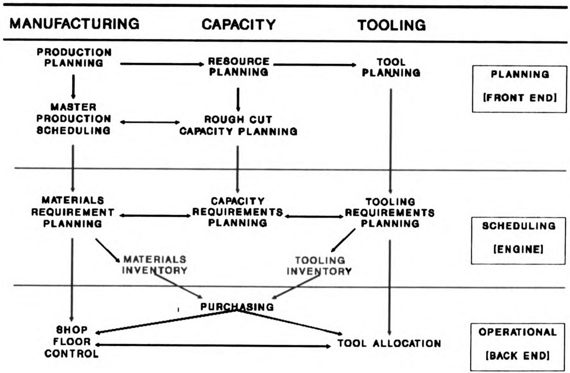
In Chapter 1, a brief discussion of tooling and its role in production was presented. Understanding that role is essential to appreciate how tooling influences manufacturing. The purpose of this chapter is to view tools within the context of a firm's overall planning and control system. This includes a comprehensive discussion of the planning and control activities necessary for tool management. Figure 3-1 presents the framework on which the discussion is based.

The first part of this chapter examines how and why a firms long-range planning must include a tooling strategy. This is especially true for such production environments as FMS and stamping and injection die shops (forming tools). Subsequent sections explore the operational aspects of tooling, including scheduling and control. Such techniques as Materials Requirement Planning (MRP) will be evaluated. Actual shop floor control of tooling also will be addressed. In addition, a major portion of the discussion will focus on analyzing different tool control scenarios.

3.2 TOOL MANAGEMENT FRAMEWORK

Traditionally, planning and control of tooling has not been viewed as part of the mainstream of production planning. Although not at issue in this research, an

Figure 3-1 Production Planning and Control



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understanding of how tooling fits into the planning process demonstrates the full extent of tooling's effect. Figure 3-1 is a variation of the manufacturing planning and control system framework developed by Vollmann, Berry, and Whybark (1988). The model breaks planning and control into three parts: manufacturing, capacity, and tooling. Looking vertically, Figure 3-1 shows planning at the top (front end), the control functions of scheduling in the middle with operations at the backend. Each segment is discussed in detail in order to explain the importance of tooling.

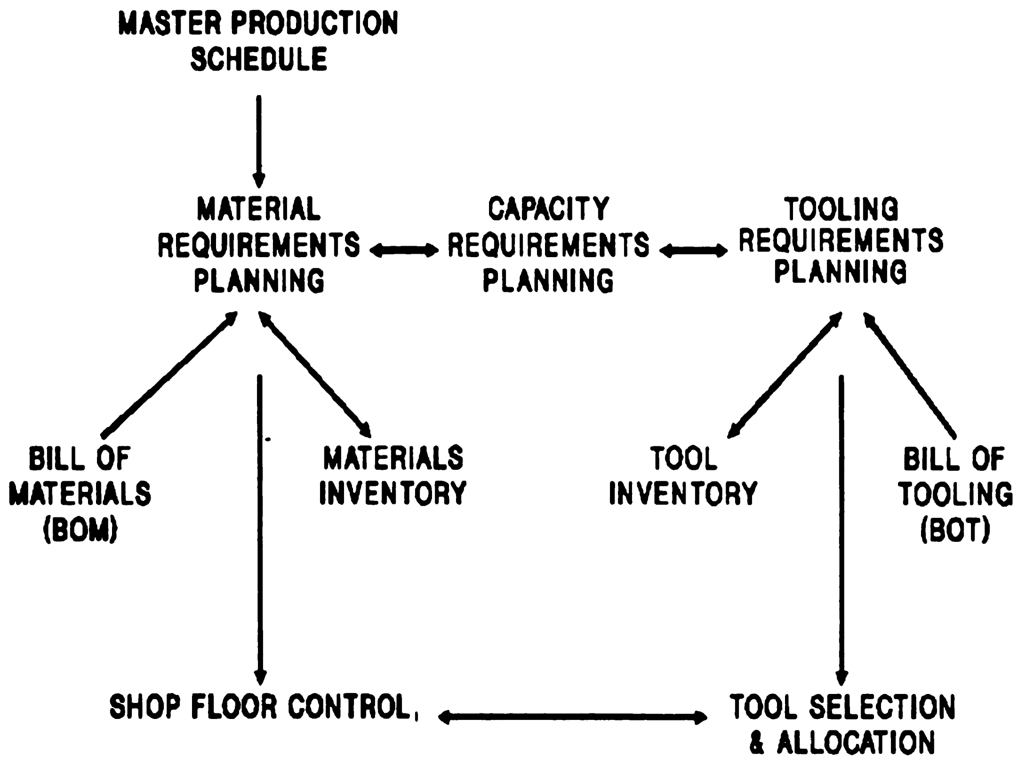
3.2.1 Planning of Tools

As noted in Figure 3-1, three areas interface at the planning level: manufacturing, capacity, and tooling. The driving force is manufacturing strategy, which determines the strategies of both capacity and tooling. At this level, planning horizons usually are long term, from a minimum of one month to more than a year. The planning process determines the length of time it takes to implement the strategies. The production plan dictates what type and how much capacity is needed. Capacity is composed of available labor, machining time, and tooling. Capacity is the link between manufacturing planning and tool planning because tooling is a determining factor in capacity (Blackburn, 1988). If any of the three capacity resources are insufficient, either more workers must be hired, more machines purchased, or additional tools obtained. The lead time for adding machines and tools may range from three months to a year, depending on the tool intricacy. The lead time may be hours for the purchase of simple cutting tools or up to six months for forming tools (Brown et al., 1981). The planning process must consider and compensate for leadtime. By preplanning capacity through the manufacturing plan, tooling needs can be integrated at an early stage, which is increasingly desirable as the manufacturing environment changes, to time-based competition. Companies must develop products more quickly (Cross, 1986; Stalk, 1988), and firms such as General Motors have adopted strategies like simultaneous engineering, JIT and other methods to accomplish this. Tools are developed at a much earlier phase in product planning to reduce the lead time for product development.

3.2.2 Scheduling of Tools

Tooling decisions are driven by the production plan through the Material Requirement Plan (MRP) schedule. The MRP schedule determines which products, and in what quantity, will be produced. However, MRP does not consider whether the necessary resources are available. These are determined by linking Capacity Requirements Planning (CRP) to MRP and then developing, detailed Tool Requirement Planning (TRP) (Wassweiler, 1982; Savoie, 1988). Figure 3-2 illustrates the process. The Bill of Tooling (BOT) defines which tools are to be used on a product and the tool life expected to be consumed at the end of processing (Gayman, 1980). It is usually expressed in processing time or number of parts produced. If this information is not on the BOT, than TRP can not track tool life. An alternative tracking method proposed by Erhorn (1983), is to combine the information on the Bill of Materials (BOM) with the BOT. In either case, the main

Figure 3-2 Tool Scheduling and Control



objective is to allow the system to plan tool requirements, monitor tool inventory, and plan tool replacement and purchases. If the amount, location, and life of tools is known, substantial savings can result (Huber, 1989; Vasilask, 1990).

In an FMS, the scheduling stage of production planning involves tool selection for the work centers' magazines. The tools placed in each magazine determine the capabilities of that work center. Under FMS, the key to production scheduling is tool allocation (Carrie and Perera, 1986). Kouvelis (1991) presents a two-level decision hierarchy that links tool scheduling with long-term production planning as a means of production scheduling.

In a traditional job or flow shop using cutting tools, production scheduling is affected by tooling to a lesser degree than under FMS. In most cases, the production schedule or MRP drives the traditional shop, not tool availability. With only minor exceptions, tooling is treated like any other inventoried material, Erhorn (1983) believes cutting tools need to be controlled with systems like MRP, but not forming tools, which are considered a capital asset and tend not to be as perishable as cutting tools. He adds that cutting tools should be controlled as inventory items, but the remaining useful life of each tool does not need to be tracked. A major benefit of Erhorn's method is that it is an inexpensive and simple way to monitor tool control. Savoie (1987) agrees with this approach because it often is impractical to track tool life.

The negative aspect of Erhorn's system is the risk of accumulating excess tools in inventory with little remaining useful life. Wassweiler (1982) advocates tracking tool usage as an inventory control method, which can be accomplished with a BOT (Wessweiler, 1982). If tool life is tracked, lower or no tool safety stocks are required (Savoie, 1987).

Unlike labor and machine time, tooling can be inventoried. This unique feature allows it to be scheduled and controlled differently than other forms of capacity. There are two common ways in which tools are inventoried. The first method treats tools as a material component controlled like any other MRP item.

This method does not consider, tool life, only the number of tools currently in inventory.

The second method is based on tracking tool life and is more costly than the first method. It may not be cost justifiable for most cutting tools. The advantage is a more accurate knowledge of available tool capacity and its current condition.

For forming tools, TRP and the scheduling process are the same as used for cutting tools. Even though Erhorn (1983) does not see the need to track and schedule nonperishable tools (forming tools), there is research that indicates otherwise (Brown, et al. 1981; Huber, 1989). TRP can be used to track tool life, which can aid in production and maintenance scheduling (Newman, 1985; Ram and Olumolade, 1987).

3.2.3 Shop Floor Control of Tools

The final stage of tool management involves detailed scheduling and selection of tools on the shop floor, where the physical removal or movement of tools takes place. Tool selection usually is random, especially when tool life is not tracked. In automated machining systems, like FMS, monitoring of internal tool wear is common, in which case random tool selection is easy and non-detrimental to system performance (Tarn and Tomizuka, 1989). That is, since tool life is being tracked, random selection is from among tools with sufficient expected life to process a job in its entirety. Usually there is only one copy of each type of forming tool, selection is not an issue.

To date, no research has addressed tool selection policies involving a tool type (that is, multiple copies of cutting tools). Intuitively, however, it seems that choice would be based on whether the tool has sufficient life to process the job fully or on some specific policy. The first policy is straight-forward, select a tool that will allow job completion without downtime for tool replacement. The second policy could include such specific policies as selection to achieve lower inventory (by using older tools first) or to reduce the risk of tool failure (by using newer tools first). Using older tools first would reduce excess tool accumulation and could incorporate a policy to replace the tool before the full tool life usage is reached (Lyman, 1993), thus reducing inventory.

Using newer tools would reduce the risk of tool failure as well as product scrap and through-put time, and machine utilization would be increased (Banerjee and Burton, 1990). An added benefit would be better use of finite storage capacity.

As noted, no studies have examined tool selection from among multiple copies. Such research is needed, and a useful extension would be to explore policies and interactions of multiple cutting tool copies under multi-tool job sequencing.

3.3 DETAILED SCHEDULING OF FORMING TOOLS

3.3.1 Tool Timing and Placement Decision

Decisions about *when* and *where* to transfer tools resemble similar issues related to labor as a resource (Nelson, 1965; Fryer, 1975; Treleven & Elvers, 1985). Whereas, past work has treated labor as a limited resource with a finite life, tools, on the other hand, need replacement or renewal (refurbishment) after a certain period of use. The finite life of tools makes them uniquely different from the labor resource. This is not to say that there are no similarities; rather, they are not fully interchangeable.

When to place a tool into production service involves control heuristics typically based on job priority. Since a job is both machine and tool specific for an operation, job heuristics determine which tool should be used next for which job. If the desired tool is not available, lost capacity may result (Mason, 1991). Thus, shop control heuristics need to be developed to reduce or eliminate the effect of lost capacity. However, to eliminate the problem would require a forward looking scheduling capability, and the linkage of capacity requirements to expectations of tool life.

The *when* tool decision looks at: (1) when to place a tool in production, (2) when to pull a tool from production, and (3) when to place a tool into maintenance. In all three cases, the *when* decision is time oriented. In the first instance, a tool is placed into production depending on demand. If a job requires a particular tool for processing, that tool type is removed from storage and placed on the machine.

Removing a tool from production depends on both the lack of demand (no job requiring the tool) and on the tool's condition. When a tool fails or comes due for PM, it is removed from production. Thus, the third instance relates to the second. Tool failure dictates the need for maintenance (CM), whereas PM usually takes place at a scheduled moment (or after an accumulated amount of processing time. PM also may occur just after tool inspection, which can take place at any time but usually is done just after a tool is pulled off the machine (when production is completed or truncated).

The tool placement decision looks at *where* to place or remove the tool in production. These *where* decisions are not as prevalent as the *when* decision because *where* issues depend on certain conditions such as tool flexibility.

Deciding *where* to place a tool involves demand for a tool type. If there is no tool flexibility between or among machines, then there is no option and *where* is not a concern. If multiple machines have a demand for a tool type, however, the issue of *where* to place a single tool copy becomes importance. This is also true if multiple tool copies have different remaining processing life. The *where* decision must analyze the tool life for each tool and job processing time. To date, no research has addressed this matter. DRC research has shown that the decision about *where* to place labor does not have a significant effect on shop performance (Treleven and Elvers, 1987), but whether this holds true for tools remains to be investigated.

3.3.2 Examples of Tool Control

Figures 3-3 a-c illustrates how tools are controlled in a shop. In Figure 3-3a, the theoretical production shop is empty and idle. There are three work centers, with four dedicated tools per work center and one maintenance center. T1-3 is tool number 3 used at machine center one. Tools that need service are sent to the

Figure 3-3a Shop Layout and Tool Control
(Tools are machine specific with no duplicate)

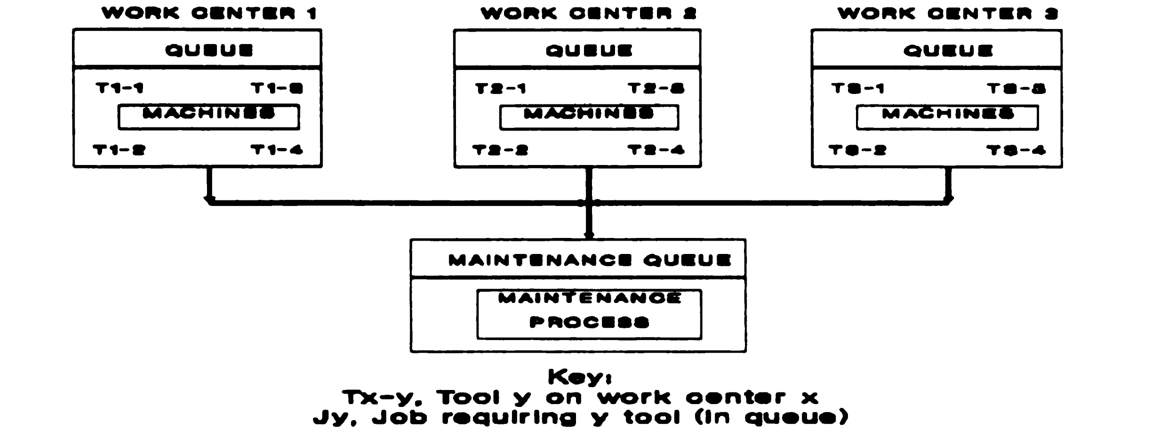


Figure 3-3b Shop Layout and Tool Control

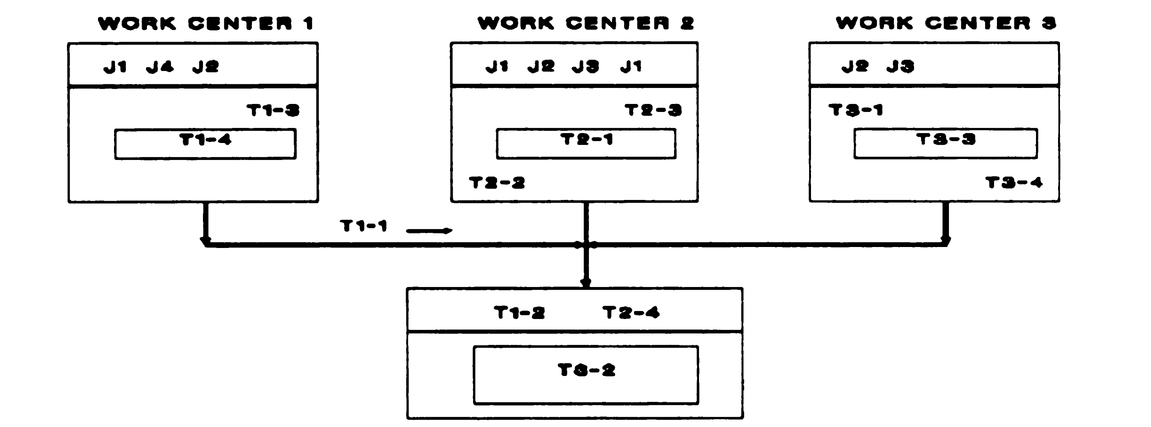
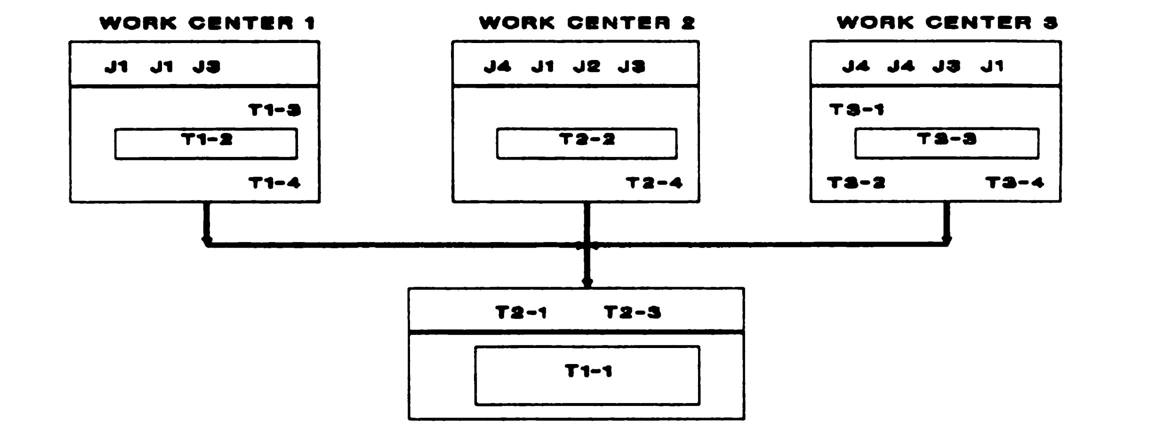


Figure 3-3c Shop Layout and Tool Control



maintenance queue and wait until capacity is available. When service is completed, the tool is sent back to its designated machine center.

Figure 3-3b shows an active production shop. Each machine has a job queue specific to each work center. J1 represents a job requiring tool number one. Looking at work center 1, the current setup is tool number 4, which the second job in the queue requires. When the current job is done processing, the tool should be changed to handle the priority job in queue, but T1-1 is on its way to maintenance facility and is not likely to be available. At work center 2, the current tool setup is number 1, which the next job in the queue (highest priority) requires, so no tool change is needed.

In Figure 3-3c, a difficult decision can be seen at work center 2. When the current job is completed, which job should be processed next? Should the tool be kept on the machine and the third job in the queue run so that a setup is avoided? Or should the tool be pulled and setup time incurred in order to process J4? The tradeoff is between the expense of an additional setup and the possibility of late delivery on a higher priority job (Mahmoodi et al., 1990). The situation at work center 3 is similar except that the two highest priority jobs require the same tool. Work center 1, the first two jobs in the queue are blocked out of production until the necessary tool is available from maintenance. Tool blocking, due to the lack of a tooling resource, is similar to the situation Goodman (1979) noted regarding labor blocking in a DRC.

Figure 3-4 a and b illustrates how tools are controlled when there is tool

Figure 3-4a Shop Floor and Tool Control
(Tool flexibility with no duplicate)

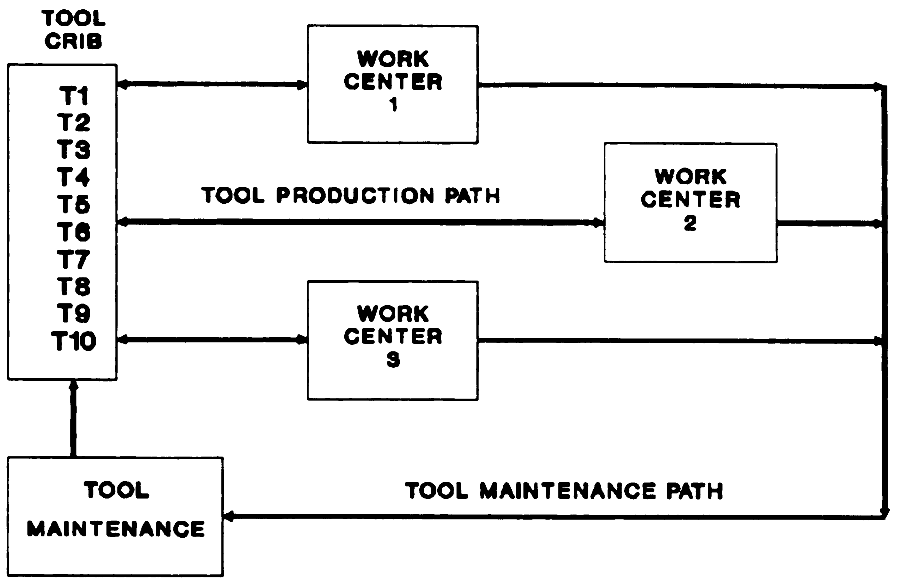
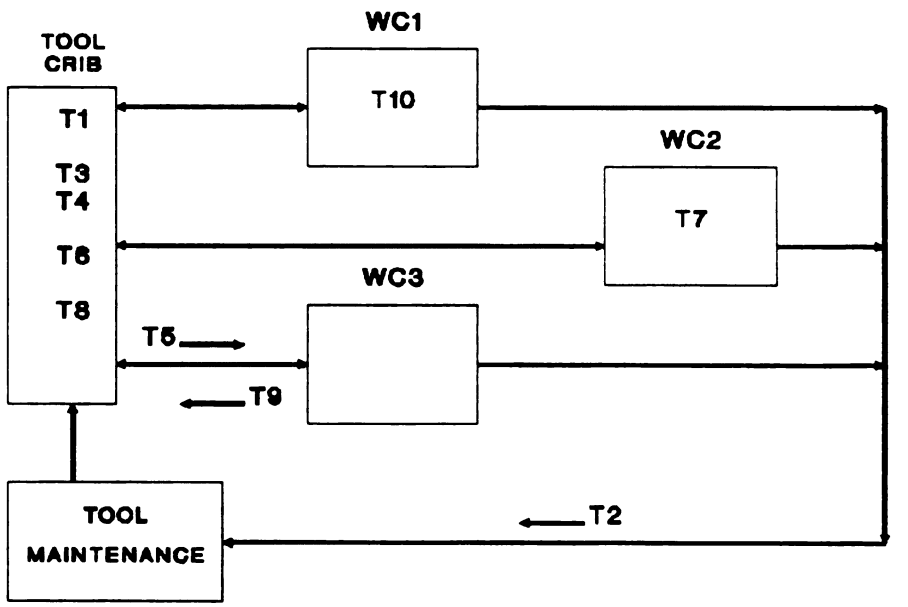


Figure 3-4b Shop Floor and Tool Control
(Tool flexibility with no duplicate)



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flexibility. From centrally controlled tool crib, tools can be assigned to any work center, so job routing flexibility is possible. As was the case in Figure 3-3, when a work center has completed a job, the tool is inspected to determine if servicing is needed. If so, the tool is sent to the maintenance center and then back to the tool crib. If not, it goes directly back to the tool crib. Depending on how jobs are released to the shop floor, it could be possible for different work centers to require the same tool simultaneously. With no duplicates for each tool type (T1 through T10), a machine can be blocked from production due to lack of available tool resource. Tool blocking is a factor in lost capacity (Mason, 1991).

Figures 3-5 a and b shows that the risk of tool blocking is reduced when there are multiple copies of each tool type. With one copy per work center, blocking due to excess demand is unlikely. Less tool blocking means less lost capacity. The tradeoff is costs, which include: increased tool investment, additional storage capacity, and a more difficult selection process. The number of duplicate tools a firm acquires can be constrained by its storage capacity and available capital. The greater the number of duplicate tools, the more complicate is the decision of which tool to select next for processing. Should older tools be chosen over newer tools, or should tool life be the criterion? This question should be addressed in future research.

Figure 3-5a Shop Floor and Tool Control
(Tool flexibility with multiple duplicates)

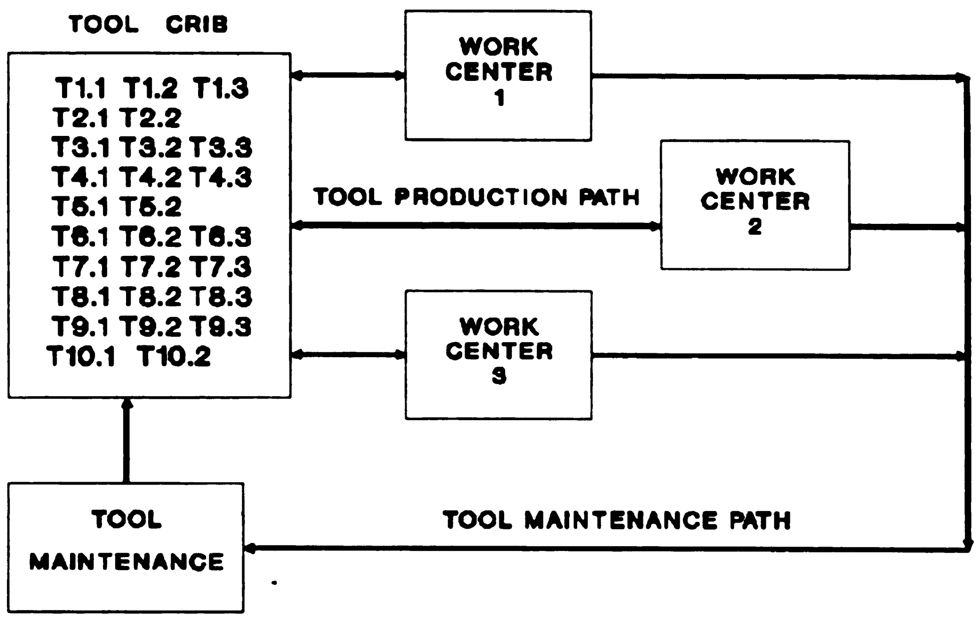
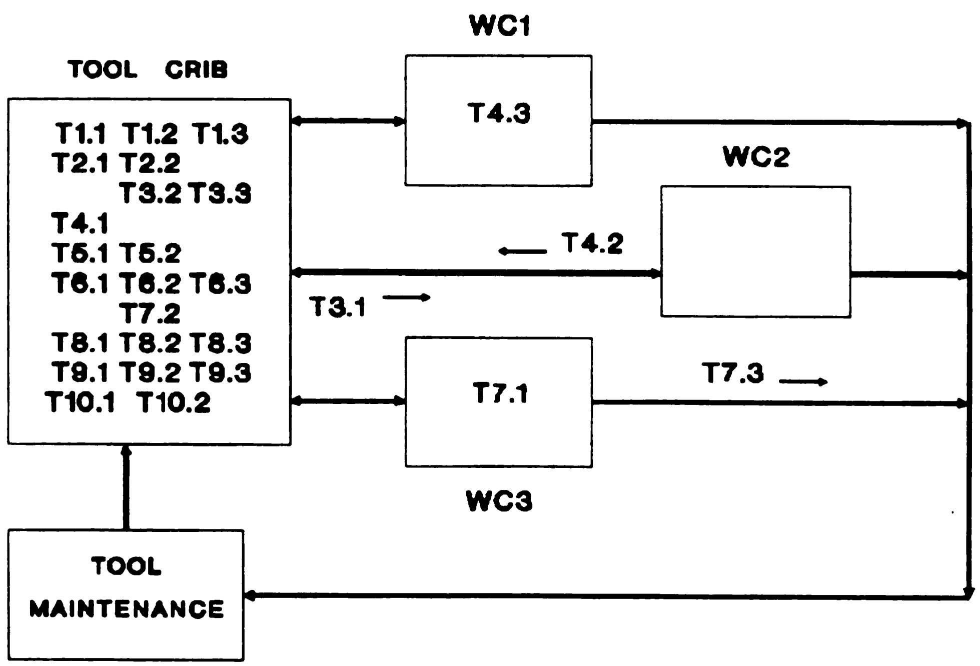


Figure 3-5b Shop Floor and Tool Control
(Tool flexibility with multiple duplicates)



CHAPTER 4

RESEARCH METHODOLOGY AND SIMULATION MODEL

4.1 INTRODUCTION

The research considered in this study focuses on experimentation in a production shop system which is machine and tool limited. Looking at either one of these resources separately gives an unrealistic view of shop scheduling. A more realistic approach is to examine each resource (machine and tool) in combination. However, this requires that the production system have both tools and machines available for processing. A vast majority of past research investigating the Dual Resource Constraint (DRC) environment has examined only machine and labor availability through dispatching rules and labor assignment (Treleven, 1989). This research differentiates itself from past research by replacing labor with tooling. The benefit of examining a DRC environment is the identification of different tooling factors which could influence shop performance.

To test the effects of finite life tooling, a simulation model is used to gather data on a hypothetical DRC flow shop. The DRC shop will be analyzed under a number of different experimental conditions. The output will then be subjected to analysis of variance (ANOVA) statistical tests for the performance measures and Tukey HSD multiple comparisons for both a priori hypotheses and post hoc tests.

The simulation method of analysis was used in order to better understand tooling and to develop effective control heuristics. In addition, several firms interviewed prior to developing the model expressed several concerns, including: 1) the need to understand how variance in tool life and maintenance service time affects the shop and 2) the need for usable and simple control procedures.

4.2 MODEL DEVELOPMENT

Proper development of a simulation experiment necessitates that several steps be initially considered. An essential part of the simulation development requires that a detailed evaluation of the model be conducted on an ongoing basis. Fishman and Kivint (1968) classify the simulation model evaluation process into three areas: 1) validation, 2) verification, and 3) problem analysis. A brief description of each is provided below with a detailed discussion presented later.

1) *Validation*: Determines if the model accurately represents the real system or environment.

2) *Verification*: The process of ensuring that the model behaves the way it was intended.

3) *Problem Analysis*: The process of drawing statistically significant inferences from the data generated by the simulation model.

The order of verification and validation is not paramount as far as research methodology is concerned (Law and Kelton, 1991). In fact, the two should proceed simultaneously throughout the model's development. Problem Analysis, on the other hand, is related to the output of the model. It can only occur after the model has been both verified and validated. Problem Analysis will be covered in Chapter 5 in

Design of Experiment section.

4.3 VALIDATION OF EXPERIMENT

The validation process attempts to answer two questions, 1) does the model behaves in the same manner as the real life system?, and 2) what inferences can be drawn from the model? An interesting component to validity is the fact that models can never be proven correct, but rather incorrect.

Cook & Campbell (1979) provide four methods which can be used as validating techniques. These consists of the following forms of validity: (1) External, (2) Construct, (3) Internal, and (4) Statistical Validity. Each of these forms of validity is discussed below in detail with respect to simulation modeling.

4.3.1 External Validity

External validity (face validity) deals with the question of whether the model represents the real world sufficiently to apply the results. One way to have external validity is if the model is based on information from an actual production environment. By using actual shop data, any conclusions drawn or policies developed can, in general, be applied to the shop. One problem with this approach is that results frequently tend to be shop specific and may not be generalized to other conditions or shops.

In developing the shop model for this research, extensive interviews were conducted. Discussions with plant managers and shop floor personnel provided insight into the workings of flow shops and job shops. Using the information derived from these interviews, a general model was developed with a high level of external validity.

4.3.2 Construct Validity

Construct validity looks at the causes and effects of manipulated variables which determine how generalizable the results are. Simulation only considers a certain number of constructs in the model. Real shops involve many more constructs. Lack of generalization is due, in part, to the limited constructs in the simulation model. This is a concern that exists when using simulation. This problem can be addressed through proper selection of relevant measures and constructs.

4.3.3 Internal Validity

Internal validity deals with the causal relationship between two measured variables. Does the independent variable cause a variation in the dependant variable? A causal relationship exists between variable X and variable Y, if Y is a direct result of X. There are several threats to internal validity which include: history, testing, instrumentation, and diffusion of treatment (Kirk, 1982). The unique feature of simulation is that it does not suffer from these concerns. The major concern of internal validity is whether the model operates correctly.

4.3.4 Statistical Conclusion Validity

The existence of co-variance between input (x) and output (y) allows for inferences to be made with regard to the model. The ability to draw conclusions or inferences about the co-variance is dependant on the following (Cook and Campbell, 1979).

- *Statistical Power*: Inadequate sample size may cause the Null hypothesis not to be rejected when there is a true significant difference in means. A minimum sample size was determined (see Section 4.4.4) to ensure sufficient power. Another means of increasing power is the reduction of irrelevant sources of variation by using common random numbers.
- *Violated Assumptions of Statistical Tests*: Certain assumptions must be met if data analysis results can be interpreted. These assumptions include: normal, identical and independently distributed (IID) variables, and homogeneity of variance (see Section 4.4). Other assumptions which affect statistical validity involves random assignment of variables and deciding if the model reaches steady state condition.
- *Fishing and the Error Rate Problem*: As the number of statistical tests increase, the probability of drawing an incorrect conclusion increases. Likewise, as the number of factors and levels in an experiment increase, so does the number of comparisons. To reduce the likelihood of a false conclusion, a larger confidence interval is needed.
- *Random Irrelevancies in the Experimental Setting*: Random features, like processing time, can affect the outcome of the dependent variables and increase estimated error. The advantage of simulation is that common random number streams are used, so that appropriate comparisons between treatment effects can be

made (Law & Kelton, 1991; Kleijnen, 1987).

4.4 SIMULATION DESIGN ISSUES

There are a number of issues which must be addressed when developing a simulation model. These included: verification, initialization bias, variance reduction, and sample size. By examining these issues, proper statistical techniques can be applied and valid inferences regarding output made.

4.4.1 Verification

As stated previously, verification is an ongoing process that should occur while the research model is being developed. Verification centers on whether the algorithms used operates correctly and whether the control procedure is modeled correctly.

Most simulation text books (Pegden, Shannon, and Sadowski, 1990; Law and Kelton, 1991; and Banks & Carson, 1984) provide the basic steps for verification of a model. The steps used for this model include:

1. Informal Analysis

Informal analysis starts with a review by individuals who possess the appropriate knowledge and abilities necessary to find errors. Use of fellow students aided in this process.

2. Structured Walkthrough

This technique is the debugging process for verification. Advance simulation software packages possess the ability to find system error and allow monitoring during initial runs. The Siman Trace command allows event by event monitoring of the model and an in-depth analysis of the flow of jobs. Furthermore, the progress of jobs were plotted to see if they meet expected results.

3. Dynamic Analysis

This technique involves verification by running the model and observing the models parameters at different levels. This stress testing pushes the model to its limits and further provides evidence that the model is working properly.

4. Comparison to Known Output

To further verify that the model is operating correctly, comparisons to other similar models can be made. This measure requires that the model have similar experimental conditions. The DRC model developed for this research cannot be compared to other models directly because of the many differences. Instead, the results were presented to the interviewed companies for their input and comparison.

Each of the techniques used for verification are iterative.

Each technique was performed on the model as needed to ensure that the model was verified.

4.4.2 Initialization Bias

Non-terminating models must be concerned with start-up conditions. Many models are started idle and empty which means that machines are free of work and there are no jobs in queue. For non-terminating systems, the initial condition is not representative of the expected operating conditions and will cause a bias in the measured parameters. Only after the model is run does it reach an equilibrium or steady state point. Until that point, the data collected is of little statistically analytic value due to bias which lower performance values. Once steady state is reached, the system exhibits long term behavior.

There are a number of techniques for reducing start-up bias [Wilson & Pritsher, 1978]. The three most recommended approaches include: A) using a long simulation run, B) truncating (discarding) a portion of the data and C) selecting initial model conditions to reduce bias.

Of these three techniques, truncation was selected due to its ease of application and effectiveness. This technique requires that the initial data be discarded. By dropping this transient data, the biased data is eliminated from the study. A good estimate of the start-up condition length is required.

Several methods were used to determine the truncation point (steady state). The first method used is the visual inspection of a graph (Pegden et al.,1990). This graphical procedure requires several replications followed by applying a moving average on the mean values (Welch, 1983). The data is then plotted graphically to see when the performance variable reaches steady state. Based on this method, it was estimated that 100 jobs would need to be truncated. While this method is simple, it lacks statistical proof that initialization bias is eliminated. For this reason, the Schruben, Singh, and Tierney (1983) technique was used.

This second method is based on the Schruben (1982) and Schruben et al.

(1983) technique for detecting the presence of initialization bias in a time series. The technique tries to determine if significant differences exist between batch means from an initial run. The data is divided into 2 parts (halves) where k < N, with the second half usually being much larger than the first. The following steps are used in detecting negative initialization bias on time in system performance measures.

Step 1. Determine the sample variance and degrees of freedom using the batched

$$var(\overline{y_N}) = \frac{\sigma^2}{N}$$

method. The degrees of freedom for t_v is equal to (n/2)-1 where n is the number of batches.

Step 2. Determine the t statistic based on Schruben et al. (1983).

$$t_v = \left(\frac{\sqrt{45}}{N^{3/2}\sigma}\right)\sum_{k=1}^{N}\left(1-\frac{k}{n}\right)k\left(\overline{Y_N}-\overline{Y_k}\right)$$

Step 3. If found not significant, the null hypothesis can be rejected, indicating no difference between Y_N and Y_k means. In addition, if the null hypothesis is rejected, than the first half of the data is dropped and another batch of jobs (next k jobs) is used as the first half. This process is repeated until the null hypothesis is accepted (Kleijnen, 1987)

The Schruben et al. (1983) technique was performed for each treatment (112 cells). The number of jobs needed to be discarded ranged from 85 to 135. The actual number of jobs discarded was 2000 for the start of each treatment run because this was the value chosen for the batch size. Truncating by batch ensures that all remaining batches are of equal size which is relevant when statistically analyzing the data.

4.4.3 Variance Reduction

The use of Common Random Numbers (CRN) as a variance reduction technique in the experimental design can improve the analysis of the results [Nelson, 1990]. CRN can also reduce the number of replications required by a model while achieving the same level of precision of the model (Pegden et al., 1990). The objective of CRN is to reduce variance in the point estimate of the mean response except for that caused by the treatment. Reducing variance allows for smaller confidence intervals of the performance measures. Smaller intervals allow for more confidence in inferences drawn from the interval.

Use of common random numbers starts with a numerical seed value for a given random number stream. The numerical seed value is the identical starting point for each treatment. A random number stream is assigned to each unique distribution (i.e. arrival time, processing time, and set up time) that requires generating a random variable. This ensures that each varied model configuration will have matched (synchronized) random numbers.

The use of CRN poses a problem through the loss of independence of samples. By not synchronizing one random number stream, independence between treatments is increased (Mihram, 1974). A total of six random number streams are used. The only random number stream not synchronized was that used for defining which machine a job would be assigned to. Arrival rate, processing time, setup time, tool life, and maintenance service time were all matched for each treatment.

Another major problem with the use of CRN is the fact that it induces autocorrelation between batches. This problem can be solved by having sufficiently large batch sizes (refer to Section 4.4.4.2).

4.4.4 Sample Size

Sample size (or run length) is a key concern for statistical analysis. An inappropriate sample size may cause biased data and a non-normal distribution. When the sample size is too small, autocorrelation becomes a factor which affects the statistical analysis. A larger sample size can resolve these issues and provide high statistical power. A pilot run for mean time in system was conducted in order to determine the sample size for each treatment condition which ensure that the effects of normality and autocorrelation did not influence the statistical analysis. A batch size of 2000 jobs was selected with 100 batches per run (treatment). This size is considered sufficient by Schmeizer (1982) for estimating confidence intervals.

4.4.4.1 Normality

Traditional statistical analysis, like ANOVA, requires that the data be normally distributed. Some variation in normality is allowed because of the robustness of ANOVA (Neter, Wasserman, & Kutner, 1990). With small batch sizes, it is less likely that observed values will be distributed normally. In simulation, data tends to be highly correlated, and thus batch sizes have to be sufficiently large for the means to be normally distributed.

Several methods can be used to determine if data is normally distributed. The simplest method is to graphically plot the output (mean of n batches) and visually inspect the results (Pegden et al., 1990; and Wilkinson, 1989). While this method was used initially, the technique lacks statistical proof.

Instead, the method used for testing normality was Filliben's (1975) probability plot correlation coefficient test. Filliben's method requires testing of the correlation of batch means by comparing them with Filliben's critical correlation tables. If the correlation of the batched means surpasses the critical value from the table, then the data is considered normal. If not, then the batch size is increased and the test repeated. After testing each experimental condition, the minimum batch size needed to ensure normality was between 900 to 1000.

4.4.4.2 Autocorrelation

Autocorrelation allows the variables of batch K to directly influence the variables of batch K + 1. The smaller the batch size, the stronger the influence. Law and Carson (1979) and Mihram (1984) suggest that the batch size be increased until they become uncorrelated. To test for autocorrelation, the Von Neumann statistic (q) (as recommended by Kleijnen (1987)) was used to test the output (flow time). The value of q can be computed as a function of the number of batch means (n). A single large batch is run and the test statistic divides the run into the greatest number of batches (n) possible without being autocorrelated. If batch means are not independent or normally distributed, then the null hypothesis is rejected and the batch size is increased. Kleijnen (1987) further recommends that a value corresponding to n=100 provides the autocorrelation test with sufficient power. Each treatment was tested using the Von Neumann test. The minimum batch size necessary to ensure that autocorrelation was not a factor was 500 jobs.

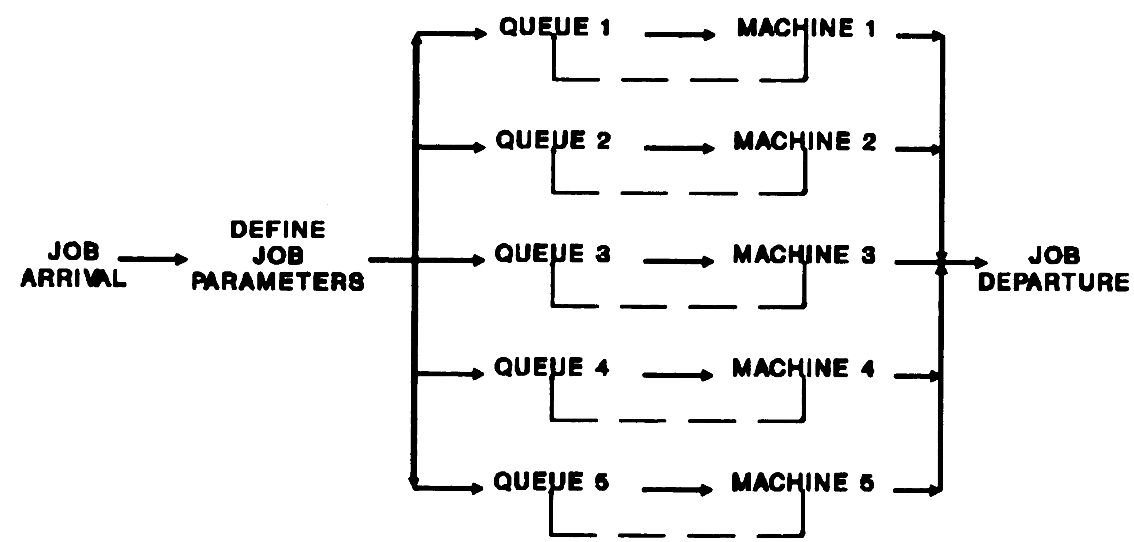
4.5 DESCRIPTION OF SIMULATION ENVIRONMENT

The simulation model is described in the following three sections. In the first section, a computer simulation using a discrete event model with user written subroutines is described. The second section discusses the control procedures for both job and tool, and the final section describes the assumptions made in the design of the model.

4.5.1 Shop Model Parameters

The simulation model is a flow shop in which identical orders (job) follow a specific path. This is in contrast to a job shop which randomly routes each job for processing. Discussions with managers from several firms showed that forming tools, common in stamping or injection model plant, tend to operate using a flow shop pattern. On the other hand, cutting tools were found to be more common in job shop environments. Since the focus of this research is on forming tools, a flow shop

Figure 4-1 Flow of Work Through the Shop



model was selected to enhance the study's external validity.

Figure 4-1 describes the sequence of events required to process a job. Jobs arrive based on a Poisson distribution at a negative exponential inter-arrival rate. Upon arrival, job attributes (parameters) are defined, including: due date, processing and setup time, and machine and tool requirements. The following sections describe each of the parameters in detail. Table 4-1 provides a summary of the values selected for the different model parameters.

Table 4-1 Summary of Simulation Environment

Parameter	Description
Job Arrival	Exponential, Mean based on 90% machine utilization
Due Date	TWK, k=7
Processing Time	Normal Distribution, Mean = 10 hrs., Std.Dev.=1.5 hr
Setup Time	Normal Distribution, Mean = 2 hrs, Std.Dev.=.2 hrs.
Actual Tool Life	Normal Distribution, Mean = 120 hrs. Std.Dev.=14.12 & 38.2
PM Point of Tool Life	Constant, 80% of Mean Tool Life
Preventive Maintenance Service Time	Log-normal Distribution with Mean of 3.0 hrs., Variance=.3 & .9
Corrective Maintenance Service Time	2.0 * Preventive Maintenance Service Time

4.5.1.1 Due Date Setting

Due date is determined by taking the jobs arrival date plus a multiple of the jobs processing time (TWK method). The following equation is used to calculate a jobs due date (Conway et al., 1967).

$$DUE\ DATE = ARRIVAL\ TIME + K*TOTAL\ PROCESSING\ TIME$$

Where: K = constant

The value for K in the TWK due date assignment procedure is a major determinate in the percentage of jobs past their due date. TWK was selected because it has been shown to be an effective method for setting a due date with respect to performance measures such as tardiness (Baker, 1984). A K value of 7 was selected which resulted in 15 to 30 percent of jobs being tardy (Lyman, 1993). Several past DRC models have also found K=7 to be a reasonable value (Melnyk & Lyman, 1991).

4.5.1.2 Processing and Setup Time

Processing and Setup time is determined from a random normal distribution. A normal distribution was chosen because demand patterns from customers tend to vary around a mean value, with equal probability and variance. Conversations with plant schedulers indicate that processing time per customer varies only slightly. It was estimated that the typical job (order) took an average of 10 hours of processing time. Once processing starts for a job, the machine runs until the job is complete (unless tool failure occurs).

Setup time was not a major factor for most plants visited because of quick die changes. Setup time ranged from a low of 3 minutes to as high as 6 hours. While most setup times were less than an hour, when it does exceed one hour, tool setups tend to be a key concern. For this reason, setup time was set at two hours (20 percent of processing time) with a normal distribution (see Table 4-1).

4.5.1.3 Machine and Tool Assignment

Machine and Tool selection defines the location where a job will be processed. The job is first randomly assigned a specific tool from a uniform distribution. Once assigned a tool, the job is assigned a machine based on Table 4-2. Table 4-2 shows that there are four tools per machine and that a tool is specific to only one machine as designated by the value of 1. A zero value designates that a tool cannot be assigned to that machine.

Table 4-2 Tool-Machine Assignment Matrix

		Machine Number				
		1	2	3	4	5
	1	1	0	0	0	0
	2	1	0	0	0	0
	3	1	0	0	0	0
	4	1	0	0	0	0
T	5	0	1	0	0	0
O	6	0	1	0	0	0
O	7	0	1	0	0	0
L	8	0	1	0	0	0
	9	0	0	1	0	0
N	10	0	0	1	0	0
U	11	0	0	1	0	0
M	12	0	0	1	0	0
B	13	0	0	0	1	0
E	14	0	0	0	1	0
R	15	0	0	0	1	0
	16	0	0	0	1	0
	17	0	0	0	0	1
	18	0	0	0	0	1
	19	0	0	0	0	1
	20	0	0	0	0	1

Once assigned a machine (based on tool requirements), the job is sent to the appropriate machine queue. The job will wait in queue until the time when it's priority establishes it as the next job for processing. The establishment of priority within a queue is part of the job priority control policies which will be discussed in Section 4.5.2. Once a job is done processing, the job then exits the system and is considered complete.

Should a tool fail while a job is being processed, the job must return to the machine queue. The job's processing time is decreased by the amount of time the tool was able to process the job. The failed tool is then sent to the maintenance queue and waits for Corrective Maintenance (CM) to be performed. The job waits in the machine queue until such time as the tool becomes available and job priority rules establish the job as the next for processing. This describes the basic workings of the simulation model. The next section will discuss how jobs are selected for processing, and the rules which determine when tools are sent in for corrective or preventative maintenance.

4.5.1.4 Dispatching Rule

Only one dispatching rule, minimum slack, was tested in this model. Minimum Slack (MINSLK) was chosen for several reasons. First, MINSLK has been shown to be a robust dispatching rule over a number of performance measures, particularly with mean and standard deviation of tardiness (Conway et al., 1967; Lyman, 1993).

The other reason for the exclusive use of the minimum slack rule was based on conversations with several plant managers, who were all using due date oriented rules. Promised delivery dates drive the production planning process throughout the plant. The choice of either Earliest Due Date (EDD) or MINSLK were considered. MINSLK was chosen because it considers a job's processing time.

4.5.1.5 Shop Control Heuristics

In a DRC model, job priority and tool control decisions must be made simultaneously. To initiate job processing, both machine and tool resources must be free (idle). Both resources can then be seized and processing started. It is this availability which is considered when establishing job priority. The specific control heuristics will be presented in Sections 4.5.2.1 and 4.5.2.2.

4.5.1.6 Mean Tool Life

The average tool life, or mean time between tool failures, is based on an arbitrary value. The arbitrary value is derived from discussions with various plant personnel and managers. From these discussions, it became clear that few firms or individuals knew with any certainty what the average time between failures were for most forming tools. Frequently, companies use a standard life value for maintenance policies which considers the number of production hours or parts produced. Even with this information, tool life ranged from as low as fifty hours to a high of one thousand hours. It was the lower bound of tool life that posed the greatest problems for shop personnel. For this reason a value of 120 hours was selected for mean tool life. Banerjee and Burton (1990) used a mean tool life (MTBF) of between 70 and 130 hours. The value of 120 hours was within their range and was considered short enough to cause significant scheduling problems.

4.5.1.7 Preventive Maintenance Point and Percentage Estimate

Preventive maintenance (PM point) is usually performed before the mean tool life. The exact time is difficult to estimate because PM is based on tool inspection procedures. For this model, sample runs will establish the exact value for the PM point. A value 20 percent (100 hours) below the mean tool life would not be unreasonable. This falls on the conservative (low frequency) side of Banerjee and Burton's (1990) PM policies.

For the variable PM heuristics, a value of 10 percent (above and below the PM point) was selected for the PM range. The value of 10 percent is equivalent to 10 hours for VARHI, VARLO, and JDDTL, and 20 hours for VARPM and MQBPM. The 10 percent value is that it corresponds to the mean processing time (10 hours). On average, half the jobs will have a processing time which is less than or equal to the variable PM range. Should a variable PM range of less than 10 percent be used, the benefits of variable PM would decrease. Future studies should examine the issue of appropriate ranges for PM time.

4.5.1.8 Maintenance Service Time

Like mean tool life, maintenance service time is based on discussions with production firms. Information on the length of maintenance service time was available for both corrective (tool failure) and preventive maintenance. A mean PM value of three hours was considered reasonable for most moderately complex forming tools. The CM service time tends to range from no difference from PM, to three times as long. The middle range (2.0 times) was agreed upon as appropriate.

This range is also consistent with past research which compare PM and CM (Kay, 1978; Banerjee and Burton, 1990).

4.5.1.9 Parameter Summary

It should be noted that several of the parameters discussed in this chapter (dispatch rules, mean tool life and service time), could also be examined as experimental factors. This research has focused on control rules under stochastic environments. Future research could examine variations of these parameters.

4.5.2 Experimental Factor Levels

Four experimental factors will be examined: job priority rules, tool control rules, tool life distributions, and service time distributions. Table 4-3 illustrates the factors and the number of levels for each factor. The following sections will describe each level within a factor.

4.5.2.1 Job Priority Heuristics

Job priority heuristics determine which job in queue will be processed next. Prior to the release of a machine and tool from production (job completion or tool failure), the machine queue is reviewed. The review process prioritizes jobs in queue by considering a number of factors including: dispatching rule, sequence dependency, and tool condition. Listed below is a detailed explanation of the four job priority heuristics. It should be noted that all heuristics must consider resource

Table 4-3 Design of Experiment

FACTORS	TREATMENTS	TREATMENT LEVELS
JOB PRIORITY HEURISTICS	DISPATCHING RULE SEQUENCE DEPENDENCY PRIORITY SETTING RULE SEQUENCE SCHEDULING & TOOL LOAD	4
TOOL CONTROL HEURISTICS	NO PM PERFORMED FIXED PM POLICY VARIABLE PM - LOW VARIABLE PM - HIGH VARIABLE PM - LOW+HIGH MAINTENANCE BACKLOG JOB DUE DATE - TOOL LIFE	7
TOOL LIFE DISTRIBUTION	LOW VARIANCE HIGH VARIANCE	2
MAINTENANCE DISTRIBUTION	LOW VARIANCE HIGH VARIANCE	2

availability for both machine and tool.

1. Dispatching Rule with Tool Condition Information (**DRTC**). Priority is given to the job with the lowest value minimum slack (MINSLK, due date minus both job processing and current time) given the tool needed has sufficient life (before PM). No consideration is given to the issue of setup changes, nor the current machine setup. The objective is to process those jobs which have the earliest due date, yet, not risk the possibility of tool failure while processing a job. This rule is an adaptation of a simple dispatching rule by considering finite tool life.

2. Sequence Dependency and Tool Condition (**SDTC**).

This rule combines the first job priority rule (DRC) with sequence dependency. Priority is given to all jobs with the current tool setup (machine setup). Should there be more than one job requiring the current tool-machine setup, then priority is based on MINSLK dispatching. The current tool setup will remain, until: 1) no jobs require the current tool, 2) the tool reaches its PM point, 3) or the tool fails. If no jobs require the current tool setup, and if the tool has not reached its PM point or failure, then this heuristic reverts back to job priority DRTC. This rule attempts to reduce the frequency of tool changes while still processing jobs based on due dates. It is an exhaustive rule which attempts to process all jobs requiring the current tool setup prior to changing tools. Such exhaustive rules have been found to be effective in past research (Mahmoodi and Dooley, 1991). The problem with exhaustive rules is that they tend to delay jobs with earlier due dates but require different tool setups.

3. Priority Setting Rule (**PSR4**).

This rule uses four levels of job priority with tool condition information. Where SDTC can inflict delays in meeting job due dates because it is exhaustive, this rule attempts to elevate this problem. PSR4 attempts to utilize current setups and reduce excessive tool changes while simultaneously considering the job's due date. Should a job become past due (negative slack), it is given priority over all other jobs regardless of the tool setup. Table 4-4 illustrates the four priorities.

As can be seen in Table 4-4, the first priority is given to past due jobs which require the current setup. Second priority is given to those negative slack jobs requiring a tool change. Jobs that are not past due are given lower priority. This includes third priority for jobs requiring the current setup, and fourth priority for jobs requiring a tool change. Melnyk et al. (1989) and Ghosh et al. (1991) found this to be an effective rule, both in flow time and due date performance. An element not considered by either Ghosh et al. or Melnyk et al., that this rule considers, is tool condition (PM point). This rule follows the same procedures as specified in SDTC. MINSLK dispatching is used when more than one job exists within a priority.

Table 4-4 Priority Levels For Job Priority Rule PSR4.

	Job Due Date Status	
Tool Setup Condition	Past Due Negative Slack	Not Past Due Positive Slack
Current Setup	1	3
Change Setup	2	4

4. Sequence Scheduling based on Tool Load (SSTL).

This rule is comparable to SDTC when sequencing jobs based on the current setup. SSTL selects the job which requires the same tool setup based on MINSLK and tool condition. However, it differs in the job selection process when a tool change takes place. An analysis of the machine queue for production time per tool is performed. The job processing time is summed for each tool. The total processing time is then compared to the remaining tool life (PM point) for each tool. Should total processing time be less than the remaining tool life, then the algorithm continues to add job processing time until either all jobs are exhausted or total processing time exceeds remaining tool life. If total processing time is greater than remaining tool life, then the algorithm subtracts the lowest priority job's processing time from total processing time for each needed tool. The closest match between processing time and tool life without exceeding the tool life (PM point) is the next tool selected for production. Jobs are then dispatched according to the MINSLK dispatching rule.

The intent of this rule is to compare production demand to tool life. This will reduce the number of tool setup changes and allow sequence dependency to consider production demand.

4.5.2.2 Tool Control Heuristics

Tool control heuristics determine when a tool is to be sent in for maintenance (CM and PM). By controlling when a tool is sent in for maintenance, the rule effectively controls tool availability. It should be noted that all tool control rules examine a single tool at a time. Listed below is a detailed explanation of the seven tool control rules.

1. No decision, allow tools to fail and perform CM (**NOPM**). The tool is removed from production only when it has failed. PM is not considered. While a penalty is incurred by a tool requiring CM, the frequency of maintenance will be less than those rules which allow for PM. Several models have found that a CM policy is preferred over PM policies (McCall, 1966).

2. Fixed Point In Time PM policy (**FPTPM**). This myopic PM policy uses a single fixed value in the maintenance decision. Any time at or after this point in time, the tool will be sent in for maintenance. If a tool is in production and the tool researches the PM point, the tool will continue processing until the job is completed. Once the job is completed, the tool is then send in for PM. If, however, the tool life is less than the PM point, the tool is kept available for production.

3. Variable PM point with Low Frequency of Maintenance (**VARLO**). This policy uses a range of time for the designated maintenance point. The range for the variable point is α*PM past the tools normal fixed PM point where $\alpha = 10\%$. With PM point being equal to 100 hours of processing time, this rule allows an extra 10 hours (100*10%) of tool usage. If the tool is past its PM point, there are two options. First, if no job exists which can utilize the extra time (past PM), then the tool is sent in for maintenance. The second option is that if there is a job which can utilize the extra tool usage, then the tool

remains in production. If the current tool life is prior to the PM point, then the tool remains in production.

The intent of this rule, as compared to FPTPM, is to allow more jobs to be processed before a tool needs maintenance. While this rule increases the risk of tool failure, a benefit is earlier job completion.

4. Variable PM point with high frequency of PM (**VARHI**). VARHI is the opposite of VARLO in that it allows a tool to be sent in for maintenance prior to the fixed PM point. The same α level is chosen (10%) as in VARLO. A tool can be pulled for PM after 90 hours (PM-PM*α) of processing time. If there exists a job which can utilize the tool for this time (up to PM point), then the tool remains in production. If tool life is equal to or past 90 hours with no job capable of utilizing the remaining time up to PM, then the tool is sent in for PM. If the tools life is less than 90 hours, the tool remains in production service.

   The objective of this tool rule is to see whether early PM improves performance over allowing a tool to continue processing. The tradeoff is, the lower risk of tool failure versus more jobs past due because of tool availability.

5. Variable PM point (**VARPM**) combines VARLO and VARHI. This rule allows for either early of late PM because the range for the maintenance decision include 90 to 110 hours. If tool life is less than 90 hours, the tool remains in

production. If the tool life is greater than or equal to 110 hours, the tool is sent in for maintenance. This leaves a 20 hour range in which the tool can remain in production or be sent in for PM. Should no jobs exist which can use this time (20 hours), then the tool is sent in for maintenance.

The purpose of this rule is to determine whether the combination of VARLO and VARHI is better than either rule alone. By allowing greater flexibility in the PM decision, the positive attributes of each rule are incorporated.

6. Maintenance Queue Backlog and variable PM point (MQBPM). This rule combines tool control VARPM with an additional consideration of the maintenance queue. This rule preempts the selection of a job which, under VARPM, would have utilized the time between 90 and 110 hours depending on maintenance queue. If the maintenance queue is empty, the tool is sent in for PM, regardless of whether a job is available to utilize the tool. The one exception to this is if there is a job past due that can utilize the tool. The tool is then used for processing. This rule is attempting to consider the possibility of quick PM turn around as a means of reducing lost tool availability. MQBPM also tends to stabilize the work load for the maintenance process.

MQBPM allows flexibility in PM decision which occurs at the shop floor. Considering tool and shop conditions when deciding PM lowers the decision making to the shop level where information is available.

7. Compare Job Due Date to Tool Life (**JDDTL**). This rule looks at the job's due date when deciding when to send a tool in for PM. JDDTL operates identically as VARLO, with the exception of jobs which are past their due dates. JDDTL keeps the tool in production until all past due jobs are processed, regardless of tool life. Once all past due jobs are completed, the tool is then sent in for PM. Processing of late jobs may take the tool life far beyond the PM point. This assumes that the tool has not failed, in which case, the tool would be sent on for CM. While this rule increases the risk of tool failure, it attempts to process jobs which are late. JDDTL is the only rule which considers the due date status of jobs.

4.5.2.3 Tool Life Distribution

Two levels of variance will be examined using a Normal distribution with a mean value of 120 hours. The first level will look at low tool life variance (LOW). The second level will consider the impact of high variance on system performance (HIGH). The two levels, low and high, allow for comparison of the impact of variance in tool life on shop performance. The LOW value corresponds to a 10 percent chance of a tool failure prior to the PM point. The HIGH value corresponds to a 30 percent chance of tool failure prior to the PM point.

4.5.2.4 Maintenance Service Time Distribution

As with tool life, maintenance service time will have two levels of variance using the log-normal distribution. The first level will examine low variance (LOW), and the second level looks at high variance (HIGH). Using these two levels, a comparison of the impact of maintenance time variance on shop performance will be examined.

4.5.3 Model Assumptions

The assumptions made in this model are similar to other hypothetical job shops. The shop is composed of five non-identical machines and twenty non-identical tools. Four tools are assigned to each machine with no flexibility or movement between machines (see Table 4-2). Table 4-5 provides the assumptions used in this research.

Table 4-5 Model Assumptions

Assumptions
Tools are machine specific, with no cross machine movement.
Once a tool fails, processing stops and the tool is sent in for maintenance.
Actual tool life is never known under a stochastic distribution.
Only tools fail, no machine failures.
Job preemption by other jobs is not allowed.
Upon tool failure, no damage occurs to either the job or machine.
Setup time is incurred only when tools are removed from a machine.
No setup time is incurred when changing jobs on a machine as long as they are using the same tool (Kannan & Lyman, 1992).

Should a tool fail while processing a job, the job's processing time is decreased by the amount of time the job was in for processing until tool failure occurred. The job's remaining processing time will consist of the unfinished portion of its total processing time. A job is not considered complete until it is fully processed.

These assumptions parallel the assumptions of past DRC research, but contain some noticeable exceptions regarding finite tool life. Parallel assumption can be found in Melnyk et al. (1989), Melnyk and Lyman (1991), Kannan and Lyman (1992), and Lyman (1993).

4.6 PERFORMANCE MEASURES

The performance measures selected in this study are those measures considered to be common means of evaluating shop performance. The use of time in system (mean and standard deviation) is a common measure of shop performance. The use of time in system measures, provide an avenue for comparison to past DRC results. For this reason, mean and standard deviation time in system measures were used.

When discussing performance criteria with the interviewed managers, they placed a high emphasis on meeting due dates. This ability to meet promised due dates has also been emphasized by other researchers (Mahmoodi et al., 1991). For this reason, the next three measures (three to five) focus on issues relating to delivery performance.

The last measure, percentage of tool failures, tracks the ratio of CM to total maintenances (CM plus PM). The uniqueness of this measure focuses on how it should help explain variations in the other five performance measures. Percentage of tool failures also allow a comparison of tool control heuristics with respect to tool failures.

The six performance measures are:

1. Mean Time in System
2. Standard Deviation of Time in System
3. Mean Tardiness
4. Standard Deviation of Tardiness
5. Percentage of Jobs Late
6. Percentage of Tool Failures

The use of cost as a performance measure was not considered due to the complex nature of forming tool costs (materials, etc.) and proprietary concerns. Future research is needed to compare the costs of corrective maintenance (CM) verses preventive maintenance (PM).

4.7 DATA COLLECTION

The simulation was conducted using SIMAN 3.5 software package on a microcomputer. Fortran subroutines were used to customize the model and to collect output data. The use of common random numbers were used for five of six random number streams to reduce variance. A batch size of 2000 jobs was used to collect data with 100 batches per run. This ensured both independence and normality so that inferences are meaningful.

4.8 SUMMARY

The hypothetical DRC flow shop proposed for this study will be examined using a simulation package. Issues pertinent to simulation methodology such as shop operations, model assumptions, parameters, and performance measures were presented. Other issues covered pertain to validity and statistical inferences (variance reduction, normality, etc.).

The hypothesis and data analysis will be covered in Chapter 5. In addition, Chapter 5 will also describe the statistical analysis of the data and residuals for normality and homogeneity of variance.

CHAPTER 5

RESEARCH HYPOTHESES AND DATA ANALYSIS

5.1 INTRODUCTION

As outlined in Chapter 1, this research will investigate the effects that a finite life resource has on a DRC shop. In addition, both job and tool heuristics which consider finite resource life have been developed to evaluate shop performance. This investigation will provide insights into how finite tool life impacts shop performance and what control methods work best under varied conditions.

The first two sections of Chapter 5 describe the questions and hypotheses that will provide the insight into the finite life resource and DRC shop that will be discussed in Chapter 6. The last section of this chapter will entail an analysis of the simulation data. This includes checking the residuals for normality and homogeneity of variance, as well as describe the data transformation process. These steps are an essential part of the process, so that conclusions regarding the hypotheses are validated.

5.2 ANALYSIS OF EFFECTS

Each of the six performance measures, as described in Chapter 4, will be statistically analyzed. This will include analysis of variance and multiple comparisons. The questions to be answered by the analysis, is what factors (main effects) significantly effect each measure. The expected results will show that all four factors do significantly effect each of the six performance measures.

Also, higher order interaction will be examined for each measure. Should higher order interactions be significant, then the use of linear contrasts will be used to aid in explaining or understanding the interaction. By examining the performance measures prior to answering the hypotheses, this will assist in the hypotheses tests and conclusions.

5.3 RESEARCH HYPOTHESES

The hypotheses to be examined are based on answers obtained from the questions developed in Section 1.3. These hypotheses were developed a priori to the simulation experiment and are non-orthogonal linear contrasts with a confidence level of 0.05 for each comparison. The following hypotheses will examine: 1) whether increased information in setting job priority for scheduling improves shop performance, 2) which maintenance policy significantly affects shop performance, and 3) whether the effects of tool and/or maintenance time alters the relative performance of the various heuristics. The expected outcome will be discussed with each specific hypothesis.

The following hypotheses will be tested using analysis of variance (ANOVA) and linear contrasts using Tukey HSD multiple comparisons. Treatment means are defined in Table 5-1 with i and j subscripts representing columns and rows from the table respectively.

Hypothesis 1: There is no significant difference between sequence dependent

Table 5-1 Treatments in Experiment: Labeled by Column, Row

		Tool Life Variance				
		Low		High		
		Maintenance Variance		Maintenance Variance		
Job Priority	Tool Control	Low	High	Low	High	ROW
DRTC	NOPM	μ_{101}	μ_{201}	μ_{301}	μ_{401}	1
	FPTPM	μ_{102}	μ_{202}	μ_{302}	μ_{402}	2
	VARLO	μ_{103}	μ_{203}	μ_{303}	μ_{403}	3
	VARHI	μ_{104}	μ_{204}	μ_{304}	μ_{404}	4
	VARPM	μ_{105}	μ_{205}	μ_{305}	μ_{405}	5
	MQBPM	μ_{106}	μ_{206}	μ_{306}	μ_{406}	6
	JDDTL	μ_{107}	μ_{207}	μ_{307}	μ_{407}	7
SDTC	NOPM	μ_{108}	μ_{208}	μ_{308}	μ_{408}	8
	FPTPM	μ_{109}	μ_{209}	μ_{309}	μ_{409}	9
	VARLO	μ_{110}	μ_{210}	μ_{310}	μ_{410}	10
	VARHI	μ_{111}	μ_{211}	μ_{311}	μ_{411}	11
	VARPM	μ_{112}	μ_{212}	μ_{312}	μ_{412}	12
	MQBPM	μ_{113}	μ_{213}	μ_{313}	μ_{413}	13
	JDDTL	μ_{114}	μ_{214}	μ_{314}	μ_{414}	14
PSR4	NOPM	μ_{115}	μ_{215}	μ_{315}	μ_{415}	15
	FPTPM	μ_{116}	μ_{216}	μ_{316}	μ_{416}	16
	VARLO	μ_{117}	μ_{217}	μ_{317}	μ_{417}	17
	VARHI	μ_{118}	μ_{218}	μ_{318}	μ_{418}	18
	VARPM	μ_{119}	μ_{219}	μ_{319}	μ_{419}	19
	MQBPM	μ_{120}	μ_{220}	μ_{320}	μ_{420}	20
	JDDTL	μ_{121}	μ_{221}	μ_{321}	μ_{421}	21
SSTL	NOPM	μ_{122}	μ_{222}	μ_{322}	μ_{422}	22
	FPTPM	μ_{123}	μ_{223}	μ_{323}	μ_{423}	23
	VARLO	μ_{124}	μ_{224}	μ_{324}	μ_{424}	24
	VARHI	μ_{125}	μ_{225}	μ_{325}	μ_{425}	25
	VARPM	μ_{136}	μ_{226}	μ_{326}	μ_{426}	26
	MQBPM	μ_{127}	μ_{227}	μ_{327}	μ_{427}	27
	JDDTL	μ_{128}	μ_{228}	μ_{328}	μ_{428}	28
	COLUMN	1	2	3	4	

job priority rules which considers job due date versus tool condition when selecting the next tool.

$$H_0: \Phi_1 = \sum_{i=1}^{8} \sum_{j=1}^{14} \mu_{ij}/28 - \sum_{i=1}^{4} \sum_{j=22}^{28} \mu_{ij}/28 = 0$$
$$H_1: \Phi_1 \neq 0$$

This hypothesis attempts to answer whether the selection of the next job for processing should be based on tool or due date, given that a tool change will take place. The objective of sequence dependent rules is to enhance performance by reducing the time consumed by setups. Job rules which reduce the number or amount of setup time have been found to improve shop performance (Mahmoodi et al., 1990, Kannan and Lyman, 1992). Consideration of tool condition (tool life) first, permits the system to fully exploit the benefits of reduced setups. A study by Lyman (1993) found that selecting jobs by looking at tool condition first enhance performance over two other rules which examined a job's due date first. The tool condition first rule, TOOLJOB, performed best for all performance measures because it tended to reduce the number of setups. Lyman's model differs from this research because tool life was deterministic with instantaneous replacement. For this reason, the question of whether the same result was true with stochastic tool life and tool maintenance delays was examined.

The expected outcome will reject the null hypothesis which indicates that considering tool condition first, before job priority, does improve flow time performance. The exception will be due date based performance measures. By placing tool condition priority over job due date, delays in jobs requiring different tools are expected.

Hypothesis 2: The addition of information, specifically late due date status and job interrelationship, does not significantly influence shop performance.

$$H_0: \Phi_2 = \sum_{i=1}^{4} \sum_{j=1}^{7} \mu_{ij}/28 = \sum_{i=1}^{4} \sum_{j=8}^{14} \mu_{ij}/28 = \sum_{i=1}^{4} \sum_{j=15}^{21} \mu_{ij}/28 = 0$$
$$H_1: \Phi_2 \neq 0$$

This hypothesis will examine what effects, if any, each incremental form of information used in job priority scheduling has on shop performance. The three job rules which select jobs based on due date, and not tool condition are compared. ANOVA will test to see if there is a significant difference between the three job priority heuristics. Multiple comparison tests compare rules and show whether additional information improves performance for job rules.

Use of information such as job interrelationships (tool requirement/sequence dependency) allow the heuristic to reduce the number of tool setups. Hollier (1968), Ghosh et al. (1991), and Lyman (1993) have shown that certain forms of information, such as job interrelationship, can enhance shop performance.

The use of due date status, like negative verse positive slack, has been shown to be effective in improving shop tardiness (Melnyk et al. 1989). This hypothesis will determine if multi-level priority information used in the job's selection (PSR4), enhances shop performance over less information intense job priority heuristics (DRTC and SDTC).

The outcome for this hypothesis is expected to show that additional information used in setting job priority due dates has a significant benefit. Thus, the null hypothesis will be rejected. By rejecting the null hypothesis, the incremental benefit of additional information in setting job priority will surpass the benefits of simplicity. In addition, results will show that PSR4 is better than SDTC, which is better than DRTC. This ranking is dependent on the specific performance measure.

Hypothesis 3: There is no significant difference between preventive maintenance (PM) and corrective maintenance (CM).

While this hypothesis seems intuitively correct and of unquestionable

$$H_0:\Phi_3=\left(\sum_{i=1}^{4}\sum_{j=2}^{7}\mu_{ij}+\sum_{i=1}^{4}\sum_{j=9}^{14}\mu_{ij}+\sum_{i=1}^{4}\sum_{j=16}^{21}\mu_{ij}+\sum_{i=1}^{4}\sum_{j=23}^{28}\mu_{ij}\right)/96$$
$$-\left(\sum_{i=1}^{4}\mu_{i1}+\sum_{i=1}^{4}\mu_{i8}+\sum_{i=1}^{4}\mu_{i15}+\sum_{i=1}^{4}\mu_{i22}\right)/16=0$$
$$H_1:\Phi_3\neq 0$$

outcome, this has not always been the case. Cases presented by Bojanowski (1984) and Christer and Whitelaw (1983) cite the benefits of preventive maintenance over corrective maintenance. The question of whether PM is preferred over CM also has been addressed by Kay (1978) and Banerjee and Burton (1990). Kay showed that if the penalty (added repair time for CM) was high enough, PM was preferred. Banerjee and Burton's model showed that, in many cases, PM decreased shop performance (flowtime) over CM. They varied the PM point and found that PM caused more delays than CM.

The expected outcome is that PM is significantly better than CM. When looking at the test hypothesis, the predicted outcome is that PM policies (FPTPM through JDDTL) are different than NOPM. Examining this question involves the use of multiple comparisons to see which PM heuristic improves performance over CM.

Hypothesis 4: There is no significant difference between using a fixed point in time for preventive maintenance versus a variable (range) time.

$$H_o: \phi_4 = \left(\sum_{i=1}^{4} \mu_{i2} + \sum_{i=1}^{4} \mu_{i9} + \sum_{i=1}^{4} \mu_{i16} + \sum_{i=1}^{4} \mu_{i23}\right)/16 - \left(\sum_{i=1}^{4}\sum_{j=3}^{5} \mu_{ij} + \sum_{i=1}^{4}\sum_{j=10}^{12} \mu_{ij} + \sum_{i=1}^{4}\sum_{j=17}^{19} \mu_{ij} + \sum_{i=1}^{4}\sum_{j=24}^{26} \mu_{ij}\right)/48 = 0$$

$$H_1: \phi_4 \neq 0$$

Several articles have modeled the PM point as fixed in time (Kay, 1976; Wells and Bryant, 1985; Banerjee and Burton, 1990). Under a fixed point in time policy, PM can only take place after the fixed point in time is reached. Banerjee and Burton (1990) tested several different fixed PM points and found that the shorter the duration between PM points, the worse the shop performed.

Discussions with several plant personnel showed a more flexible policy. The PM point was only a target or reference point. Scheduled PM dates tended to vary around the designated PM point, depending on demand. This hypothesis will be used to determine if a fixed PM point (FPTPM) performs as well as a variable PM point (VARLO, VARHI, and VARPM).

The expected outcome rejects the null hypothesis. This would add credence to the shop personnel use of flexible PM points. The reason the null is rejected is because variable PM considers job demand in queue. If work exists for the tool, VARLO and VARPM allow temporary postponement of the PM point, while FPTPM does not. Also, VARHI and VARPM allow early PM if no demand exist for the tool. Early PM can result in higher tool availability when production demand exist.

Hypothesis 5: There is no significant difference between early (VARHI) and postponed (VARLO) variable preventive maintenance policies.

$$H_0:\Phi_5=\Big(\sum_{i=1}^{4}\mu_{i3}+\sum_{i=1}^{4}\mu_{i10}+\sum_{i=1}^{4}\mu_{i17}+\sum_{i=1}^{4}\mu_{i24}\Big)/16$$
$$-\Big(\sum_{i=1}^{4}\mu_{i4}+\sum_{i=1}^{4}\mu_{i11}+\sum_{i=1}^{4}\mu_{i18}+\sum_{i=1}^{4}\mu_{i25}\Big)/16=0$$
$$H_1:\Phi_5\neq 0$$

This hypothesis explores whether the policies of early tool withdrawal verses postponed removal perform differently. Hypothesis 5 extends hypothesis 4 by exploring the differences which exist between variable PM policies. An issue that became apparent during the plant trip interviews was the lack of a clearly defined range for the variable PM point. Since past research has not examined this issue, hypothesis 5 will determine whether there is a significant difference between performing PM early or late.

The difference between the early variable PM (VARHI) from the postponed or late PM rule (VARLO) involves risk. VARLO increases the risk of tool failure because the PM point is surpassed if the tool is needed. The benefit is a greater utilization of the tool's full life. The risk is the down time due to tool failure.

Results will show that the added risk is beneficial and thus rejects the null hypothesis. VARLO adds sufficient benefits over the added risk of tool failure.

Hypothesis 6: The preventive maintenance policy which examines maintenance queue performs significantly better than the variable preventive maintenance policies, which does not.

This hypothesis tests whether the addition of maintenance queue information

$$H_0 : \Phi_6 = \left(\sum_{i=1}^{4}\sum_{j=3}^{5}\mu_{ij} + \sum_{i=1}^{4}\sum_{j=10}^{12}\mu_{ij} + \sum_{i=1}^{4}\sum_{j=17}^{19}\mu_{ij} + \sum_{i=1}^{4}\sum_{j=24}^{26}\mu_{ij}\right)/48$$
$$-\left(\sum_{i=1}^{4}\mu_{i6} + \sum_{i=1}^{4}\mu_{i13} + \sum_{i=1}^{4}\mu_{i20} + \sum_{i=1}^{4}\mu_{i27}\right)/16 = 0$$
$$H_1 : \Phi_6 \neq 0$$

in the PM decision helps elevate performance over the basic variable PM rule (VARPM). Pate-Cornell et al. (1987) showed that unplanned early maintenance was beneficial only when the shop was stable. Unplanned early maintenance performance deteriorates quickly when shop variability (demand and maintenance time) increased. The MQBPM rule attempts to elevate the impact of variability by reducing maintenance delay. By allowing early maintenance only when the maintenance queue is empty, tool maintenance delays are reduced.

Expected results will show that the null hypothesis will be rejected. This will demonstrate that early PM based on maintenance queue can be beneficial. The frequency of PM will increase slightly with the result of decreased maintenance delay. Past studies by Banerjee and Burton (1990) and Pate-Cornell et al. (1987) have shown that increased PM frequency causes shop performance to decrease. The reason for this was that the models did not explicitly consider maintenance delays.

Hypothesis 7: The use of job due date in the decision of when to perform PM significantly improve shop performance.

As with hypothesis 6, this hypothesis tests whether additional information in

$$H_0 : \phi_7 = \left(\sum_{i=1}^{4} \mu_{i2} + \sum_{i=1}^{4} \mu_{i9} + \sum_{i=1}^{4} \mu_{i16} + \sum_{i=1}^{4} \mu_{i23}\right)/16 - \left(\sum_{i=1}^{4} \mu_{i7} + \sum_{i=1}^{4} \mu_{i14} + \sum_{i=1}^{4} \mu_{i21} + \sum_{i=1}^{4} \mu_{i28}\right)/16 = 0$$

$$H_1 : \phi_7 \neq 0$$

the PM decision is beneficial. The additional information in this case is the status (negative slack) of job's in queue. With due dates being so critical a factor in customer satisfaction, JDDTL rule is an attempt to enhance delivery performance. The rule delays PM in favor of processing past due jobs. In effect, JDDTL is increasing the risk of tool failure for the gains in improved delivery performance.

The expected outcome will show that the gains in delivery performance outweigh the drawbacks of higher risk of tool failure (reject null hypothesis). By considering issues external to the tool condition, information will improve shop performance.

Hypothesis 8: There is no significant difference between the performance of the shop under low or high tool life variance.

$$H_0: \phi_8 = (\sum_{i=1}^{2} \sum_{j=1}^{28} \mu_{ij})/56 - (\sum_{i=3}^{4} \sum_{j=1}^{28} \mu_{ij})/56 = 0$$
$$H_1: \phi_8 \neq 0$$

Hypothesis 8 tests whether tool life variance impacts shop performance. The expected outcome is that tool life variance will significantly affect shop performance, rejecting the null hypothesis. The variability of tool life will cause increased tool failures that will result in the deterioration of all performance measures. Tool failures will decrease tool availability. Past research has shown that lower tool availability significantly impacts shop performance (Melnyk et al., 1989; Ghosh et al., 1991).

Hypothesis 9: There is no significant difference between the high or low maintenance service time variance.

$$H_0: \phi_9 = (\sum_{j=1}^{28} \mu_1 j + \sum_{j=1}^{28} \mu_3 j)/56 - (\sum_{j=1}^{28} \mu_2 j + \sum_{j=1}^{28} \mu_4 j)/56 = 0$$
$$H_1: \phi_9 \neq 0$$

As in hypothesis 8, this hypothesis test will determine if maintenance service time significantly impacts performance under high and low variance. As is the case with tool life variance, maintenance time variance can play an important role in shop performance (Banerjee and Burton, 1990). Maintenance service time represents tool down time (availability). As the down time variance increases, system performance decreases (Vanderhenst et al., 1981), because tools are less available for production. Variance increases maintenance queue causing greater waiting delays and lowers tool availability. The expected outcome will be to reject the null hypothesis which indicates that maintenance time is a significant factor in shop performance.

The nine hypotheses just discussed are based on the issues and questions presented in Chapter 1. Table 5-2 shows the progression from the initial research issues to hypotheses. Each step in the process involves refinement of the questions until they become a focused hypothesis. The answers to these hypotheses can then be directed back to the initial research question: **How do we effective manage operation in a DRC shop where the tooling constraint has a finite life and where resource life and resource renewal are described using stochastic distribution?**

5.4 POST HOC ANALYSIS

Hypotheses 8 and 9 address whether tool life and maintenance variance are significant factors. What they do not consider is the impact of these two forms of variance on the relative performance of the various heuristic. The <u>post hoc</u> analysis will examine the relative performance and thus, determine the robustness of the various heuristics. The use of multiple comparisons will assist in this analysis.

5.4.1 <u>Tool Life Variance Analysis</u>

By examining the relative performance of tool and job heuristics under two

Table 5-2 Refinement of Research Issues to Hypotheses.

Issues	Questions	Hypotheses
How do we schedule jobs?	How does additional information used in setting job priority affect shop performance?	There is no significant difference between job priority rules which considers job due date before tool condition versus the a rule that looks at tool condition first, then job's due date.
		The addition of information, like late due date status and job interrelationship, does not significantly influence shop performance.
How do we schedule tools for production and maintenance?	Does PM enhance performance over CM?	There is no significant difference between preventive maintenance and corrective maintenance.
	How do various PM policies affect shop performance?	There is no significant difference between using a fixed point in time for preventive maintenance versus a variable (range) time.
		There is no significant difference between early (VARHI) and postponed (VARLO) variable preventive maintenance policies.
		The preventive maintenance policy which examines maintenance queue performs significantly better than other variable preventive maintenance policies.
		The use of job due date in the decision of when to perform PM significantly improve shop performance.
How does variation in resource life and renewal affect scheduling and assignment decisions?	Does variance in tool life and maintenance time affect the relative performance of different job priority and tool control heuristics?	There is no significant difference between shop performance under low or high tool life variance.
		There is no significant difference between shop performance under low or high maintenance service time variance.

levels of tool life variance, the robustness of the rules can be established. The objective is to find out whether rules which consider more information in their decision process perform as well under higher or lower tool life variation. This objective is achieved by comparing job priority and tool control heuristics for low tool life variance, to the relative performance of the heuristics for high variance. Any change in relative performance indicates the rules are sensitive to tool life variance.

Tool control heuristics which tend to increase tool failure risk (VARLO, VARPM, and JDDTL) will diminish in the relative performance with increased tool life variance. This conclusion is based on Levi and Rossetto (1978) and Bon (1980) who determined that conservative tool strategies (reduce tool failure risk) remain effective as tool life variance increases. Also, Vanderhenst et al. (1981) found that strategies which increase CM over PM caused shop performance to deteriorate.

5.4.2 Maintenance Service Variance Analysis

The objective is to determine which rules are robust under maintenance time variance. Job and tool heuristics will be compared under low and high maintenance variance. Any change in relative performance indicates the rules are sensitive to tool life variance, thus, lacks robustness.

Job priority heuristic do not consider the maintenance process in establishing priority. Thus, the relative ranking of job priority rules will not likely be effected.

As for tool control heuristics, maintenance service time variance will alter the relative performance. MQBPM explicitly considers maintenance backlog and should improve its relative performance as variance of maintenance time increases. JDDTL, on the other hand, causes an increased risk of tool failure, thus higher maintenance time lowers its performance. In addition, any rules (VARHI and VARPM) which cause more frequent PM's will increase in the relative performance to other rules (Banerjee and Burton, 1990).

5.4.3 Job-Tool Interaction Analysis

The objective of this analysis is to determine which combination of job and tool rules provides robust performance. By examining the combined rules, it will become apparent which factors, job priority or tool control, influences the relative performance for each specific measure. Also, results will show how the different combination of rules can alter the relative performance of either a good performing job or tool rule.

5.5 DATA ANALYSIS PROCEDURES

Once the data for each experimental condition has been collected, the data is analyzed to determine if it meets certain conditions for the statistical tests to be valid. These conditions or assumptions must be met before the research questions and a prior hypotheses and post hoc analysis can be performed. A check of the residuals for normality and homogeneity of variance is done to ensure that ANOVA and other statistical tests are valid. For the data that violate these assumptions, transformation using one of three methods was selected.

The validity of ANOVA is dependant on normality and homogeneity of variance and, thus, requires additional analysis to ensure that the statistical tests are meaningful. Minor violations of these assumptions do not preclude the use of ANOVA (Neter et al., 1990). Should the residuals be non-normally distributed (by a minor amount), the impact is a small decrease in the tests power. The implications of reduced power occurs when the ANOVA p values are close to .05, resulting in false conclusions.

5.5.1 Testing for Normality

To test for the assumptions of normality, the residuals were first analyzed using a normal probability plot. The plot pits expected values against residuals. While this method is helpful, it does not provide statistical proof. For this reason, each treatment was tested using Filliben's (1975) Probability Correlation Coefficient Test (PCCT). The test uses the normal probability plot correlation coefficient which is the product moment correlation coefficient between the ordered observation residual X and ordered statistic medians M, which forms a normal distribution. The rationale behind this test is that normality will tend to yield near linear normal probability plots which will give near unity values for the probability plot correlation coefficient. Comparison of the correlation with percentage points from the normal probability plot correlation coefficient is evaluated. A statistically significant correlation indicates that the data is normally distributed.

5.5.2 Testing for Homogeneity of Variance

Bartlett's test was used to test for homogeneity of variance. The test determines if there is a significant difference between sample variances. A major concern for Bartlett's test is any departure of the residuals from normality. In such cases, Bartlett's test can not be considered valid. If the performance measures were non-normally distributed, the data was transformed and retested. The statistical package SPSS 5.1 uses Barlett's test as its mean for testing homogeneity of variance.

5.5.3 Transformation of Data

Should either assumption of normality or homogeneity of variance be violated, the data for that performance measure was transformed. Neter et al. (1990) recommends transforming data using one of three methods: log, square root, or reciprocal. All three methods are used and the best method which provides a normal distribution for residual is selected.

5.5.4 Residual Analysis

Each treatment residual was examined for normality and homogeneity of variance. The subscript values from Table 5-1 will be used as the treatment reference for the following discussion.

For mean time in system, all but twelve treatments (301, 307, 308, 315, 322, 328, 401, 407, 408, 415, 422, 428) were normally distributed. The twelve combinations of rules were all within 4% of what was required to accept the hypothesis of normality. All but five (301, 307, 407, 415, 428) of the twelve treatments had residual variances that were homogenous. Those treatments that were heterogenous were among the worst performers for this measure.

For standard deviation of time in system, all but four treatments (314, 328, 414, 428) were non-normally distributed. These four treatments had PCCT values within 3% of that required to accept the hypothesis of normality. All treatments had equal variances for the residuals.

For mean tardiness, all treatment residuals were normally distributed. Twenty treatments (102, 107, 114, 122, 128, 201, 207, 222, 228, 301, 307, 314, 322, 401, 407, 409, 410, 414, 422, 428) had heterogenous variance, but once again they were among the worse performers.

For standard deviation of tardiness, all but fifteen treatments had normally distributed residuals. Of these non-normal treatments, eight (102, 109, 209, 307, 309, 328, 405, 407) had PCCT values within 2% of that required to accept the hypothesis of normality. The remaining seven (107, 207, 114, 128, 214, 314, 414) were within 7% of the critical value. As for homogeneity of variance, only a few treatments (110, 128, 227, 315, 327, 415, 427) violated this assumption and were not among the top performers.

For percentage of jobs late, all but twenty four treatments had normally distributed residuals. Seventeen of the non-normally distributed treatments (103, 108, 116, 120, 124, 203, 208, 216, 220, 224, 305, 308, 316, 324, 403, 405, 408) were within 5% of the critical value. The remaining seven treatments (201, 303, 330, 405, 416, 420, 424) were within 7% of the critical value. The heterogenous variances again came from treatments (115, 116, 120, 121, 203, 216, 220, 221, 315, 321, 330, 403, 415, 421) which performed poorly.

For percentage of tool failures, only 41 treatments had normally distributed residuals, with another 11 having PCCT values within 6% of the critical value. With so few treatments normally distributed, the data was transformed. Of the three methods used, log transformation significantly improved the fit of the data. Thirty one treatments were non-normally distributed, but twenty six (102, 103, 107, 109, 110, 112, 114, 116, 121, 123, 124, 126, 128, 202, 203, 209, 307, 221, 228, 302, 323, 324, 326, 328, 402, 428) had PCCT values within 3% of that required to accept the hypothesis of normality. The remaining five treatments (303, 321, 403, 409, 421) were within 6% of the critical value. Again, the treatments which violate the assumption of homogeneity of variance tend to be poor performers (103, 107, 203, 207, 222, 223, 228, 322, 403, 407, 421, 423, 428).

5.5.5 Data Analysis Summary

The impact of non-normal residual distributions cause a small increase in the significance level while decreasing the power of the ANOVA test slightly. The large sample size used in this model reduces the significance of non-normality. This also hold true for heterogeneity of variance. ANOVA is still valid even when minor violations in these assumptions are present. Only when p values are close to .05 will false conclusion likely results. As for the large violations of the ANOVA assumptions (percentage of tool failures), the data was transformed.

5.6 SUMMARY

This chapter discussed the issues and questions that the model will examine in Chapter 6. A full factorial design was used in analyzing the model. A priori hypotheses is presented with an explanation and expected outcome. In the next chapter, the use of ANOVA and Tukey HSD multiple comparisons will be used to test the hypotheses and answer questions that were developed.

CHAPTER 6

EXPERIMENTAL ANALYSIS AND CONCLUSIONS

6.1 INTRODUCTION

After assuring the assumptions of ANOVA were not violated in Chapter 5, this chapter will use three parts to analyze the data. This includes:

1. The significance of the main effects and interactions for each performance measure. This will include both statistical (ANOVA tables) and graphical (figures) analysis. Examining the questions of which factors significantly impact performance will assist the hypotheses test. The identification of specific heuristics and conditions which improve performance will be made.

2. The a priori hypotheses, which were expressed as non-orthogonal linear contrasts, will require the use of multiple comparisons in their analysis if higher order interactions are present. All of the hypotheses compare treatments (levels) within a factor. While ANOVA will detect differences (main effect significance), it does not lend itself to comparisons of levels within a factor. For this reason, multiple comparisons will be used in the analysis.

3. Post hoc analysis will require further use of multiple comparisons. Specific issues relating to the interactions of factors (tool control rules with job priority rules under different variance) will be analyzed. The objective is to provide

insight into performance patterns of the various heuristics.

Upon completion of the analysis, specific conclusions will be drawn. This includes a comparison to past research as well as new findings. The last part of this chapter will discuss the direction that future research should consider.

6.2 ANALYSIS OF EFFECTS FOR PERFORMANCE MEASURES

The results presented are based on a full factorial design consisting of 112 treatment conditions. All statistical tests were performed with a confidence level (α) of .05. The statistical package, SPSS 5.01 for Windows, was used to perform all tests.

Common random number streams, as described in Chapter 4, are used as a blocking factor in ANOVA. If the blocking variable is significant, experimental error variance is reduced (Neter et al., 1990). NBATCH was used as the blocking factor. If significant, then the batches are independent which is a requirement of ANOVA. In the ANOVA tests performed, NBATCH is significant for all performance measures which demonstrates higher levels of treatment independence (Mihram, 1974). The following discussion will examine the ANOVA tables and figures (graphs) for each performance measure. Also provided is the treatment means from which the figures are derived.

6.2.1 <u>Mean Time in System</u>

Table 6-1 contain the ANOVA results for time in system. Only two main

Table 6-1 Analysis of Variance for Mean Time in System

Source of Variation	S	D	MS	F	p
BATCH	146741.96	99	16304.66	4279.71	.000
MTOOL	9385.46	6	1564.24	410.59	.000
NLIFE	6.23	1	6.23	1.63	.201
NRULE	331.71	3	110.57	29.02	.000
NSERVE	.01	1	.01	.00	.971
MTOOL*NLIFE	146.09	6	24.35	6.39	.000
MTOOL*NRULE	311.13	18	17.28	4.54	.000
MTOOL*NSERVE	10.28	6	1.71	.45	.845
NLIFE*NRULE	10.12	3	3.37	.89	.448
NLIFE*NSERVE	.34	1	.34	.09	.765
NRULE*NSERVE	2.96	3	.99	.26	.855
MTOOL*NLIFE*NRULE	71.20	18	3.96	1.04	.413
MTOOL*NRULE*NSERVE	22.13	18	1.23	.32	.997
NLIFE*NRULE*NSERVE	1.52	3	.51	.13	.940
MTOOL*NLIFE*NSERVE	10.19	6	1.70	.45	.848
MTOOL*NLIFE*NRULE*NSERVE	41.45	17	2.44	.64	.862
(Model)	159429.2	119	1339.74	351.66	.000
(Total)	163239.02	11199	145.88		
R-Squared =	.977				
Adjusted R-Squared =	.974				

effects, tool control rules (MTOOL) and job priority rules (NRULE), are significant. The higher order interactions of MTOOL by NRULE and MTOOL by NLIFE were also significant. All other main effects and interaction are not significant. Figure 6-1(a-d) illustrate how the different tool control rules and job priority rules influence mean time in system. The figures show that tool control rules cause more fluctuations in performance than other factors. Those tool rules which provide greater PM flexibility, such as VARHI, VARPM, and MQBPM, reduce mean time in system. This holds true for all tool life and maintenance time variances. The worst performing tool control rule is NOPM.

As for job priority rules, SSTL consistently performs worse than any of the other job rules. This holds for most tool control rules or variance levels. The best

Table 6-2 Treatment Mean for Mean Time in System

TOOL/MAINT VARIABILITY	JOB RULE	NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	61.90	56.28	58.29	53.27	54.80	54.42	59.21
	SDTC	63.39	56.18	58.96	53.55	53.67	53.44	59.77
	PSR4	62.99	60.77	58.98	53.37	54.76	53.33	56.82
	SSTL	66.04	56.34	59.78	53.96	56.65	54.17	60.47
TOOL-HIGH MAINT-LOW	DRTC	62.67	57.77	59.39	54.71	55.61	54.48	60.05
	SDTC	65.80	58.27	59.53	54.29	54.70	54.24	59.57
	PSR4	62.29	57.68	58.76	54.54	55.74	54.15	58.41
	SSTL	64.04	58.58	59.99	55.02	56.77	54.55	60.98
TOOL-LOW MAINT-HIGH	DRTC	62.07	55.46	58.32	53.27	54.96	54.90	59.73
	SDTC	64.42	56.87	58.98	53.55	53.67	53.44	58.80
	PSR4	63.33	55.50	58.65	53.37	54.73	53.32	57.79
	SSTL	66.69	56.41	59.44	53.93	56.66	54.27	61.35
TOOL-HIGH MAINT-HIGH	DRTC	62.71	58.27	58.21	55.55	55.59	54.55	59.78
	SDTC	63.36	59.03	59.10	54.30	54.70	54.07	60.25
	PSR4	63.10	57.72	59.77	54.54	55.04	54.12	58.57
	SSTL	63.76	58.57	59.84	55.59	57.39	54.41	62.13

Legend:

Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.

Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.

TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

performing job priority rule is PSR4, followed by DRTC (Table 6-2). However, this rule does not hold true in all cases (Figures 6-1 a-d).

Figure 6-1a Comparison of Control Rules
Low Tool/Low Maintenance Variance

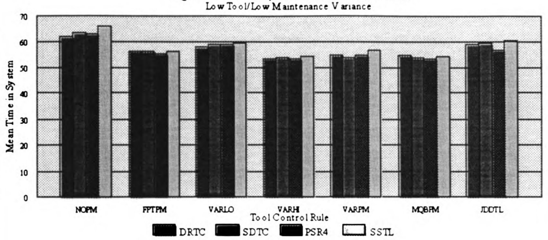


Figure 6-1b Comparison of Control Rules
High Tool/Low Maintenance Variance

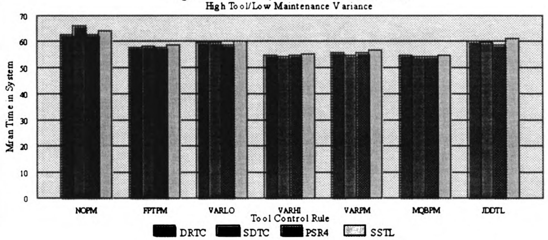


Figure 6-1c Comparison of Control Rules

Low Tool/High Maintenance Variance

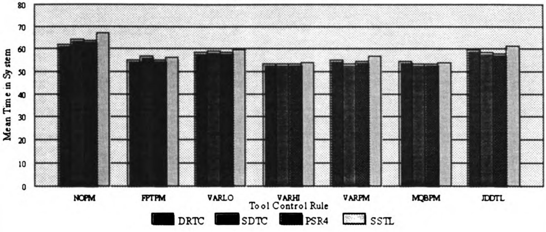
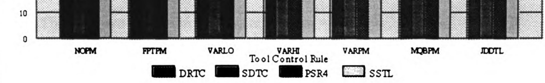


Figure 6-1d Comparison of Control Rules

High Tool/High Maintenance Variance



6.2.2 Standard Deviation of Time in System

Table 6-3 Analysis of Variance for Standard Deviation of Time in System

Source of Variation	S	D	MS	F	p
BATCH	290635.78	99	32292.86	3127.17	.000
MTOOL	14698.24	6	2449.71	237.22	.000
NLIFE	7.15	1	7.15	.69	.405
NRULE	19202.93	3	6400.98	619.86	.000
NSERVE	.00	1	.00	.00	.993
MTOOL*NLIFE	98.00	6	16.33	1.58	.149
MTOOL*NRULE	8758.29	18	486.57	47.12	.000
MTOOL*NSERVE	18.21	6	3.04	.29	.940
NLIFE*NRULE	10.57	3	3.52	.34	.796
NLIFE*NSERVE	.31	1	.31	.03	.862
NRULE*NSERVE	.83	3	.28	.03	.994
MTOOL*NLIFE*NRULE	123.12	18	6.84	.66	.850
MTOOL*NRULE*NSERVE	137.48	18	7.64	.74	.772
NLIFE*NRULE*NSERVE	1.42	3	.47	.05	.987
MTOOL*NLIFE*NSERVE	36.25	6	6.04	.59	.742
MTOOL*NLIFE*NRULE*NSERVE	149.65	17	8.80	.85	.632
(Model)	341908.01	119	2873.18	278.23	.000
(Total)	352234.56	11199	314.78		
R-Squared =	.971				
Adjusted R-Squared =	.967				

The ANOVA Table 6-3 provides an analysis for standard deviation of time in system. The main effects of MTOOL and NRULE are significant as well as higher order interactions between MTOOL and NRULE. All other main effects and interactions are not significant. Figures 6-2 (a-d) show that job priority rules which are due date based (DRTC and PSR4) cause less variation (standard deviation) in the time in system than rules which promote sequence dependency (SDTC and SSTL).

The standard deviation of time in system is reduced by tool control rules which promote more frequent (early) PM (Table 6-4). Figures 6-2 (a-d) show that the combination of job due date based priority rules with frequent PM tool rules consistently provide better performance. This combination includes: DRTC with

Table 6-4 Treatment Means for Standard Deviation for Time in System

TOOL/MAINT VARIABILITY	JOB RULE	TOOL RULES NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	46.46	55.77	44.95	40.88	42.79	48.42	59.50
	SDTC	57.79	60.46	55.33	49.37	50.21	50.12	65.53
	PSR4	47.47	45.99	49.26	43.95	46.67	44.02	48.57
	SSTL	64.57	56.29	55.55	54.35	53.39	52.38	63.41
TOOL-HIGH MAINT-LOW	DRTC	46.08	57.80	45.71	41.95	43.46	46.14	61.87
	SDTC	61.57	60.98	56.20	50.27	51.38	51.16	63.44
	PSR4	47.29	47.36	49.01	45.34	47.26	44.81	48.87
	SSTL	65.33	58.57	55.01	55.91	52.84	55.78	65.64
TOOL-LOW MAINT-HIGH	DRTC	45.95	54.63	44.98	40.88	42.99	49.67	62.14
	SDTC	59.55	60.59	55.34	49.37	50.21	50.06	64.17
	PSR4	47.43	46.01	48.81	43.95	46.60	44.07	49.34
	SSTL	65.34	56.24	55.85	54.04	53.45	51.58	64.08
TOOL-HIGH MAINT-HIGH	DRTC	45.99	57.43	43.97	43.35	57.17	49.47	62.40
	SDTC	57.90	62.88	54.91	50.29	51.44	50.91	65.22
	PSR4	47.64	47.34	49.02	45.32	46.69	45.21	48.82
	SSTL	63.72	58.89	55.70	57.16	54.28	53.07	63.94

Legend:
Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.
Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.
TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

VARHI, MQBPM, VARLO, and VARPM; and PSR4 with VARHI and MQBPM.

Figure 6-2a Comparison of Control Rules

Low Tool/Low Maintenance Variance

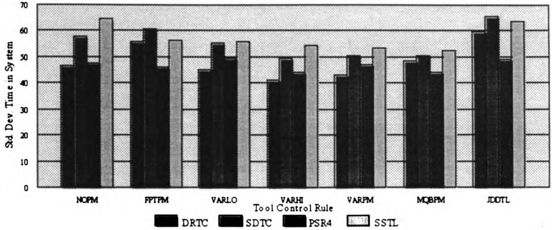
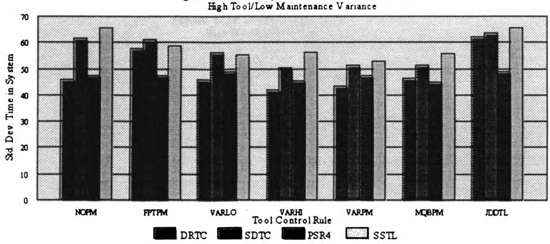


Figure 6-2b Comparison of Control Rules

High Tool/Low Maintenance Variance



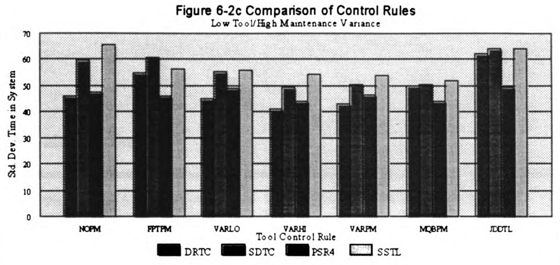


Figure 6-2c Comparison of Control Rules
Low Tool/High Maintenance Variance
Std. Dev. Time in System
0
10
20
30
40
50
60
70
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

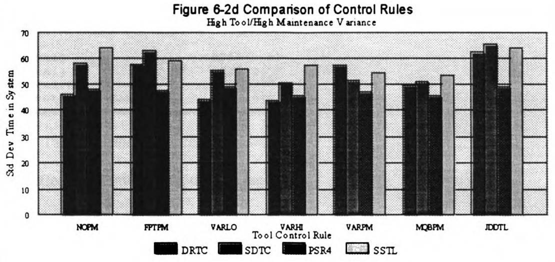


Figure 6-2d Comparison of Control Rules
High Tool/High Maintenance Variance
Std Dev Time in System
0
10
20
30
40
50
60
70
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

The tool control rule, JDDTL, consistently caused poorer performance when combined with all, but PSR4 job priority rules. Tool rule, NOPM, also performed poorly when combined with sequence dependent rules SDTC and SSTL (Figure 6-2a).

6.2.3 Mean Tardiness

Table 6-5 Analysis of Variance for Mean Tardiness

Source of Variation	S	D	MS	F	p
BATCH	432155.42	99	48017.27	3241.60	.000
MTOOL	37338.53	6	6223.09	420.11	.000
NLIFE	8.41	1	8.41	.57	.451
NRULE	105296.46	3	35098.82	2369.49	.000
NSERVE	1.18	1	1.18	.08	.778
MTOOL*NLIFE	186.09	6	31.01	2.09	.052
MTOOL*NRULE	23867.35	18	1325.96	89.51	.000
MTOOL*NSERVE	71.98	6	12.00	.81	.562
NLIFE*NRULE	11.56	3	3.85	.26	.854
NLIFE*NSERVE	.83	1	.83	.06	.813
NRULE*NSERVE	1.20	3	.40	.03	.994
MTOOL*NLIFE*NRULE	303.71	18	16.87	1.14	.308
MTOOL*NRULE*NSERVE	137.89	18	7.66	.52	.951
NLIFE*NRULE*NSERVE	.16	3	.05	.00	1.000
MTOOL*NLIFE*NSERVE	24.38	6	4.06	.27	.949
MTOOL*NLIFE*NRULE*NSERVE	267.48	17	15.73	1.06	.387
(Model)	609399.55	119	5121.00	345.71	.000
(Total)	624212.39	11199	557.83		
R-Squared =	.976				
Adjusted R-Squared =	.973				

Table 6-5 shows the results of the ANOVA test for mean tardiness. The only main effects and interactions that are significant is MTOOL and NRULE and MTOOL by NRULE. Figures 6-3 (a-d) show that due date oriented job priority rules (DRTC and PSR4) tend to lower mean tardiness more than sequence dependant rules (SDTC and SSTL). The PSR4 rule performed best among job priority rules (Table 6-6). The figures also illustrate how SDTC and SSTL rules are consistently poor

Table 6-6 Treatment Means for Mean Tardiness

TOOL/MAINT VARIABILITY	JOB RULE	TOOL RULES						
		NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	44.61	61.39	43.52	38.64	40.74	41.95	69.79
	SDTC	59.35	65.30	60.23	52.90	53.61	54.17	72.84
	PSR4	41.25	35.73	40.45	34.45	37.56	34.35	37.74
	SSTL	70.21	61.67	59.40	58.38	57.59	53.57	73.99
TOOL-HIGH MAINT-LOW	DRTC	44.10	66.64	44.09	39.59	41.48	39.57	73.27
	SDTC	64.97	65.79	59.92	53.61	55.17	54.56	68.81
	PSR4	41.05	37.98	39.87	36.98	38.65	35.62	38.30
	SSTL	71.79	63.68	58.20	59.12	57.14	56.00	77.20
TOOL-LOW MAINT-HIGH	DRTC	43.54	63.86	43.55	38.64	40.96	43.60	73.79
	SDTC	62.27	65.21	60.16	52.90	53.61	53.66	72.77
	PSR4	41.03	36.07	39.91	34.45	37.71	34.24	40.12
	SSTL	70.76	63.05	59.72	58.39	57.55	53.85	74.75
TOOL-HIGH MAINT-HIGH	DRTC	44.83	65.09	42.26	41.27	59.93	41.29	74.79
	SDTC	60.17	68.24	58.75	53.76	55.48	54.60	71.64
	PSR4	41.58	37.24	39.92	36.96	38.07	35.72	39.08
	SSTL	70.69	66.10	59.13	59.93	58.21	55.50	74.50

Legend:

Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.

Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.

TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

performers. This holds for all tool control rules.

When tool control rules were combined with job priority rules, DRTC,

Figure 6-3a Comparison of Control Rules

Low Tool/Low Maintenance Variance

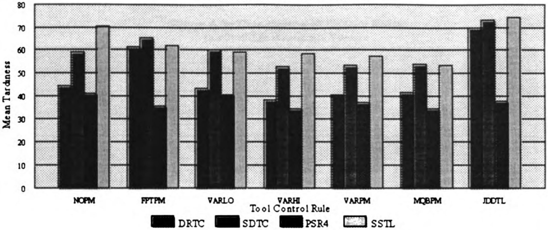
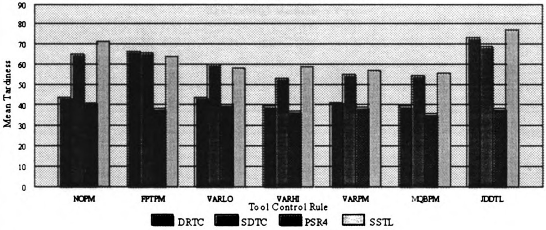


Figure 6-3b Comparison of Control Rules

High Tool/Low Maintenance Variance



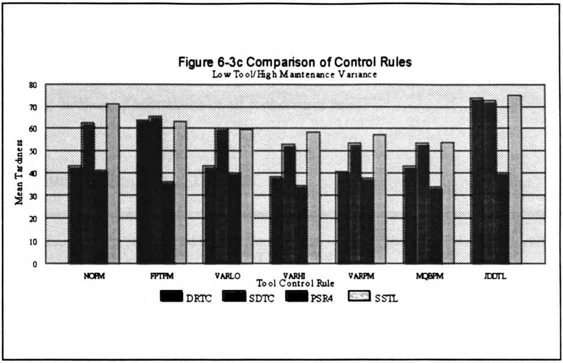


Figure 6-3c Comparison of Control Rules
Low Tool/High Maintenance Variance
Mean Tardiness
80
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

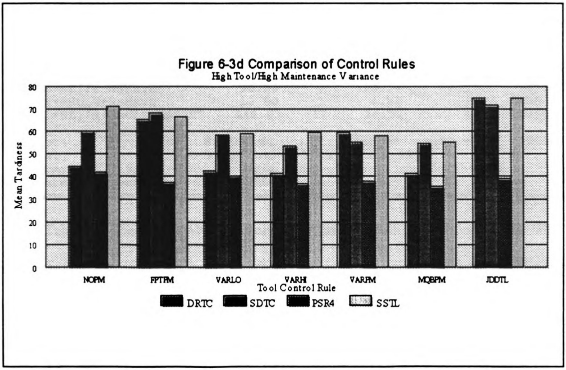


Figure 6-3d Comparison of Control Rules
High Tool/High Maintenance Variance
Mean Tardiness
80
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

SDTC, and SSTL, results showed that flexible PM point rules (VARHI and VARPM) work better than when combined with FPTPM or NOPM tool rules. The exception to this situation involves the PSR4 job rule. The PSR4 rule tends to equalize tardiness performance of all tool control rules.

6.2.4 Standard Deviation of Tardiness

Table 6-7 Analysis of Variance for Standard Deviation of Tardiness

Source of Variation	S	D	MS	F	p
BATCH	710918.21	99	78990.91	1932.57	.000
MTOOL	43265.75	6	7210.96	176.42	.000
NLIFE	23.11	1	23.11	.57	.452
NRULE	71851.41	3	23950.47	585.96	.000
NSERVE	.01	1	.01	.00	.985
MTOOL*NLIFE	191.34	6	31.89	.78	.585
MTOOL*NRULE	35981.86	18	1998.99	48.91	.000
MTOOL*NSERVE	48.12	6	8.02	.20	.978
NLIFE*NRULE	169.78	3	56.59	1.38	.246
NRULE*NSERVE	14.51	3	4.84	.12	.949
NLIFE*NSERVE	.43	1	.43	.01	.919
MTOOL*NLIFE*NRULE	521.23	18	28.96	.71	.805
MTOOL*NRULE*NSERVE	588.13	18	32.67	.80	.703
MTOOL*NLIFE*NSERVE	90.85	6	15.14	.37	.898
NLIFE*NRULE*NSERVE	13.60	3	4.53	.11	.954
MTOOL*NLIFE*NRULE*NSERVE	445.63	17	26.21	.64	.860
(Model)	884508.81	119	7432.85	181.85	.000
(Total)	925382.40	11199	826.97		
R-Squared =	.956				
Adjusted R-Squared =	.951				

Table 6-7 shows the ANOVA results for standard deviation of tardiness. The only significant main effects and interactions are MTOOL, NRULE, and NRULE by MTOOL respectively. The due date based job priority rules, DRTC and PSR4, perform better than sequence dependent rules SDTC and SSTL (Table 6-8). As was the case with mean tardiness, the PSR4 job rule provides consistent performance,

Table 6-8 Treatment Means for Standard Deviation of Tardiness

TOOL/MAINT VARIABILITY	JOB RULE	TOOL RULES						
		NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	39.62	63.74	38.10	34.42	37.57	51.51	67.41
	SDTC	58.21	74.68	57.07	50.10	52.65	52.80	78.70
	PSR4	38.61	42.45	46.29	39.76	44.93	40.29	46.83
	SSTL	64.76	61.17	58.18	64.65	57.28	61.56	69.07
TOOL-HIGH MAINT-LOW	DRTC	38.77	69.13	39.36	35.45	37.58	47.38	72.03
	SDTC	63.77	73.54	58.32	51.15	54.06	54.41	76.79
	PSR4	38.37	43.14	46.11	41.95	44.90	41.12	46.44
	SSTL	69.64	64.01	57.54	66.44	56.15	70.43	74.27
TOOL-LOW MAINT-HIGH	DRTC	38.62	63.03	38.10	34.42	37.77	53.73	71.27
	SDTC	60.86	73.62	57.03	50.10	52.65	52.68	77.28
	PSR4	38.31	42.32	45.77	39.76	44.51	40.38	47.73
	SSTL	64.88	60.82	59.49	64.14	57.37	59.54	70.12
TOOL-HIGH MAINT-HIGH	DRTC	38.39	67.31	36.69	37.55	68.94	55.85	73.22
	SDTC	58.96	76.14	56.17	51.11	54.10	53.58	79.77
	PSR4	38.31	43.50	46.16	41.87	44.15	42.23	46.06
	SSTL	66.20	64.26	59.07	68.94	58.20	64.22	69.42

Legend:

Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.

Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.

TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

regardless of the tool control rule used (Figure 6-4a). The worst performing job

Figure 6-4a Comparison of Control Rules

Low Tool/Low Maintenance Variance

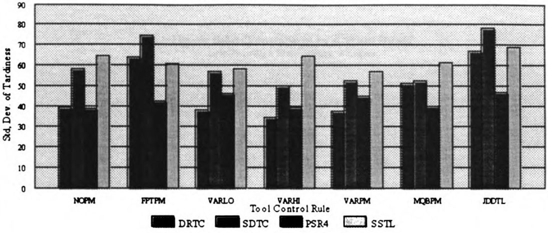
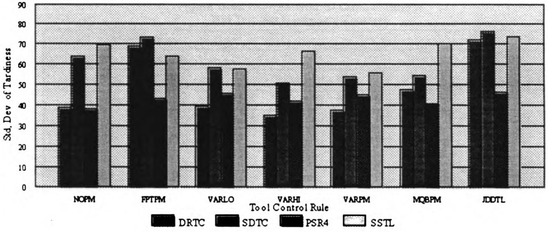


Figure 6-4b Comparison of Control Rules

High Tool/Low Maintenance Variance



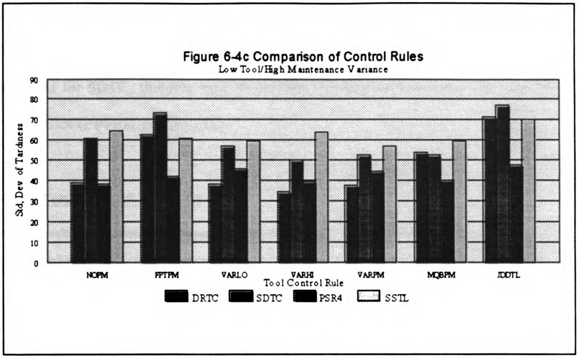


Figure 6-4c Comparison of Control Rules
Low Tool/High Maintenance Variance
Std, Dev of Tardiness
90
80
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

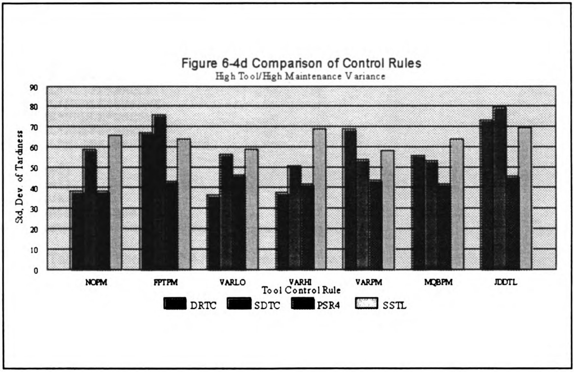


Figure 6-4d Comparison of Control Rules
High Tool/High Maintenance Variance
Std, Dev. of Tardiness
90
80
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

priority rule was SSTL.

Variable PM tool control rules, VARHI, VARLO, and VARPM, performed best when combined with due date job priority rules DRTC and PSR4 (Figures 6-4 a-d). As for SDTC, this rule tends to perform worse when combined with fixed PM point rules (FPTPM and JDDTL).

6.2.5 Percentage of Jobs Late

Table 6-9 Analysis of Variance for Percentage of Jobs Late

Source of Variation	S	D	MS	F	p
BATCH	.51	99	.06	53.27	.000
MTOOL	106.90	6	17.82	16780.70	.000
NLIFE	.03	1	.03	31.39	.000
NRULE	.16	3	.05	49.01	.000
NSERVE	.00	1	.00	.01	.925
MTOOL*NLIFE	.81	6	.14	127.55	.000
MTOOL*NRULE	.33	18	.02	17.17	.000
MTOOL*NSERVE	.00	6	.00	.07	.999
NLIFE*NRULE	.00	3	.00	.19	.903
NLIFE*NSERVE	.00	1	.00	.01	.911
NRULE*NSERVE	.00	3	.00	.04	.990
MTOOL*NLIFE*NRULE	.01	18	.00	.54	.942
MTOOL*NRULE*NSERVE	.00	18	.00	.05	1.000
NLIFE*NRULE*NSERVE	.00	3	.00	.00	1.000
MTOOL*NLIFE*NSERVE	.00	6	.00	.07	.999
MTOOL*NLIFE*NRULE*NSERVE	.00	17	.00	.04	1.000
(Model)	125.69	119	1.06	994.82	.000
(Total)	126.75	11199	.11		
R-Squared =		.992			
Adjusted R-Squared =		.991			

Table 6-9 shows the ANOVA results for percentage of jobs late. All the main effects, except NSERVE, are significant. The higher order interactions of MTOOL by NLIFE and MTOOL by NRULE are also significant. The sequence dependent rules, SDTC and SSTL, provide lower percentage of jobs late for most treatments.

Table 6-10 Treatment Means for Percentage of Jobs Late

TOOL/MAINT VARIABILITY	JOB RULE	TOOL RULES						
		NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	33.1	24.3	30.2	26.3	27.4	27.0	25.2
	SDTC	31.4	24.2	27.5	24.7	24.6	24.3	25.4
	PSR4	38.3	33.1	34.8	31.4	31.7	31.2	34.3
	SSTL	32.2	25.9	28.6	24.0	26.5	24.2	26.5
TOOL-HIGH MAINT-LOW	DRTC	34.0	24.0	31.1	27.9	28.3	27.9	24.7
	SDTC	32.2	25.8	28.3	25.2	25.3	24.9	26.4
	PSR4	37.7	35.1	35.0	31.7	32.4	31.7	35.3
	SSTL	30.1	27.1	29.1	24.5	26.6	24.0	26.3
TOOL-LOW MAINT-HIGH	DRTC	33.8	23.2	30.2	26.3	27.6	27.0	24.7
	SDTC	31.6	24.9	27.6	24.7	24.6	24.4	24.9
	PSR4	38.8	33.1	34.7	31.4	31.7	31.3	34.3
	SSTL	32.3	25.4	28.1	23.8	26.5	24.2	27.1
TOOL-HIGH MAINT-HIGH	DRTC	33.8	24.8	30.7	28.2	24.9	27.7	24.0
	SDTC	31.0	25.8	27.9	25.2	25.3	24.8	26.1
	PSR4	38.3	35.1	35.0	31.6	31.8	31.5	35.3
	SSTL	29.9	26.2	28.8	24.9	27.0	24.0	27.8

Legend:
Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.
Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.
TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

The PSR4 job priority rule performs worse than any other job rule. This is a sharp contrast to PSR4's performance on mean and standard deviation of tardiness. The

Figure 6-5a Comparison of Control Rules

Low Tool/Low Maintenance Variance

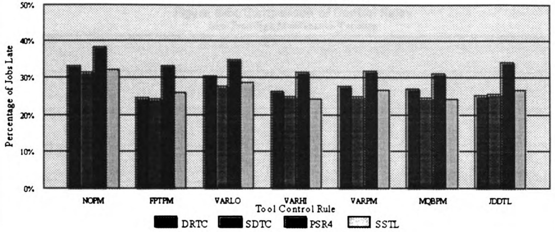
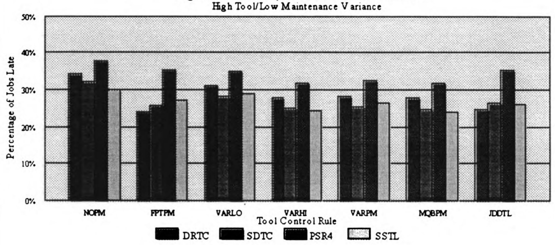


Figure 6-5b Comparison of Control Rules

High Tool/Low Maintenance Variance



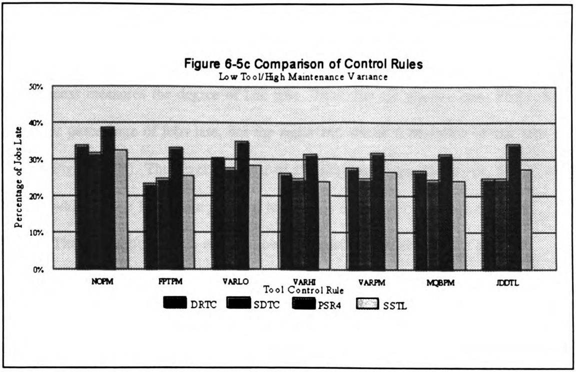


Figure 6-5c Comparison of Control Rules
Low Tool/High Maintenance Variance
50%
40%
30%
20%
10%
0%
Percentage of Jobs Late
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

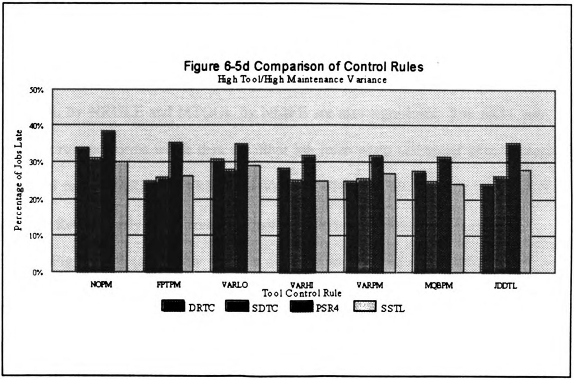


Figure 6-5d Comparison of Control Rules
High Tool/High Maintenance Variance
50%
40%
30%
20%
10%
0%
Percentage of Jobs Late
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

reason for the abrupt difference between tardiness measures and percentage of jobs late involves the specifics of the measure. The percentage of jobs late measurement only counts whether a job is late or not. Whereas, the mean and standard deviation of tardiness measures the degree of late jobs. Thus, the job priority rule, PSR4, has a greater percentage of jobs late, but the mean and standard deviation of late jobs is lower (Figure 6-5a). The reverse is true of the sequence dependent rules, SDTC and SSTL, which cause fewer late jobs but tend to be much later (Figures 6-5 a-d).

The tool control rules which allow PM perform better than the tool rule NOPM (Table 6-10). The best performing tool control rules are those which promote early PM (VARHI, VARPM, and MQBPM).

6.2.6 Percentage of Tool Failures

Table 6-11 shows the ANOVA results for log percentage of tool failure. All the main effects, except NSERVE, are significant. The higher order interactions of MTOOL by NRULE and MTOOL by NLIFE are also significant. The SSTL job priority rule performs worse than the other job rules when combined with the service PM tool rules: VARLO, VARHI, and VARPM (Table 6-12). The job rule, DRTC, also performs poorly when combined with MQBPM and JDDTL tool rules.

Figures 6-6 (a-d) show how the different tool control rules perform for percentage of tool failures. The tool control rule, NOPM, causes 100 percent tool failure, as expected. The tool control rules, VARLO, JDDTL, and FPTPM, all have higher levels of tool failure. These tool rules do not provide for early PM as do the

Table 6-11 Analysis of Variance for the Log of Percentage of Tool Failures

Source of Variation	S	D	MS	F	p
BATCH	4.42	99	.49	41.11	.000
MTOOL	238.66	6	39.78	3326.38	.000
NLIFE	.89	1	.89	74.83	.000
NRULE	1.58	3	.53	43.96	.000
NSERVE	.00	1	.00	.22	.638
MTOOL*NLIFE	2.28	6	.38	31.74	.000
MTOOL*NRULE	4.84	18	.27	22.50	.000
MTOOL*NSERVE	.00	6	.00	.07	.999
NLIFE*NRULE	.00	3	.00	.11	.955
NLIFE*NSERVE	.00	1	.00	.41	.524
NRULE*NSERVE	.00	3	.00	.11	.957
MTOOL*NLIFE*NRULE	.28	16	.02	1.48	.100
MTOOL*NLIFE*NSERVE	.01	6	.00	.12	.994
MTOOL*NRULE*NSERVE	.03	18	.00	.15	1.000
NLIFE*NRULE*NSERVE	.00	3	.00	.08	.972
MTOOL*NLIFE*NRULE*NSERVE	.01	15	.00	.03	1.000
(Model)	450.55	119	3.92	327.63	.000
(Total)	460.58	11199	.48		
R-Squared =	.978				
Adjusted R-Squared =	.975				

rules: VARHI, VARPM, and MQBPM (Figure 6-6a). Another feature of these tool control rules is, they all deteriorate in performance as tool life variance increases (Figures 6-6 a-b).

6.2.7 Analysis of Effects Summary

The following is a summary of the significant effects for the six performance measures.

- The main effects of tool control rules (MTOOL) and job priority rules (NRULE) is significant for all performance measures. Table 6-13 provides a synopsis of the ANOVA test results for significant main effects and interaction.

\- The higher order interaction between tool control rules (MTOOL) and job priority

Table 6-12 Treatment Means for Percentage of Tool Failures

TOOL/MAINT VARIABILITY	JOB RULE	TOOL RULES NOPM	FPTPM	VARLO	VARHI	VARPM	MQBPM	JDDTL
TOOL-LOW MAINT-LOW	DRTC	100	17.2	46.3	0.2	3.0	0.4	37.4
	SDTC	100	17.5	39.6	0.1	0.3	0.0	33.3
	PSR4	100	16.8	44.7	0.3	2.0	0.0	29.6
	SSTL	100	16.9	53.7	0.3	6.0	0.2	36.5
TOOL-HIGH MAINT-LOW	DRTC	100	33.5	49.5	2.6	4.1	1.3	46.7
	SDTC	100	33.9	43.8	1.6	1.9	0.8	42.2
	PSR4	100	33.0	47.5	2.0	3.5	0.8	39.5
	SSTL	100	33.0	54.3	3.1	7.3	0.8	45.9
TOOL-LOW MAINT-HIGH	DRTC	100	17.4	46.3	0.2	3.1	0.3	37.8
	SDTC	100	17.1	39.6	0.1	0.3	0.0	33.2
	PSR4	100	17.3	44.4	0.3	2.0	0.0	29.7
	SSTL	100	16.6	53.6	0.2	5.9	0.2	36.4
TOOL-HIGH MAINT-HIGH	DRTC	100	32.9	49.5	4.2	2.9	1.0	46.3
	SDTC	100	32.7	44.7	1.6	1.9	0.7	42.8
	PSR4	100	32.9	47.8	2.0	3.4	0.6	40.6
	SSTL	100	33.3	54.3	2.9	6.9	0.8	46.0

Legend:

Tool Control Rules: NOPM - no PM performed, allow tool to fail.
FPTPM - fixed PM point, PM occurs only after PM point.
VARLO - variable PM point, allow postponed PM up to 10% beyond.
VARHI - variable PM point, allow early PM up to 10% before.
VARPM - variable PM point, allow early or postponed PM, 10%.
MQBPM - use VARPM rule but consider maintenance queue
JDDTL - use FPTPM but consider job due date.

Job Priority Rules: DRTC - prioritized by due date
SDTC - prioritized by sequence dependency, then due date.
PSR4 - prioritized using four priority levels
SSTL - prioritized by sequence dependency, then by tool condition.

TOOL-LOW: low tool life variance.
TOOL-HIGH: high tool life variance.
MAINT-LOW: low maintenance service time variance.
MAINT-HIGH: high maintenance service time variance.

rules (NRULE) is significant for all performance measures.

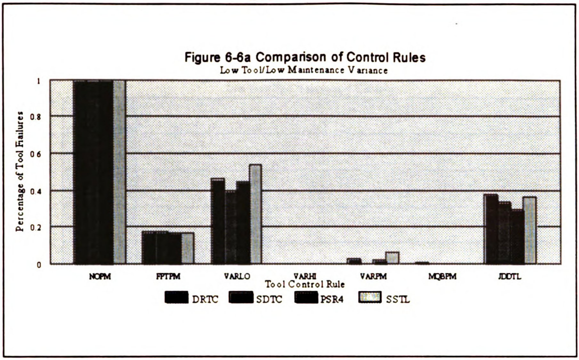


Figure 6-6a Comparison of Control Rules
Low Tool/Low Maintenance Variance
Percentage of Tool Failures
1
0.8
0.6
0.4
0.2
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

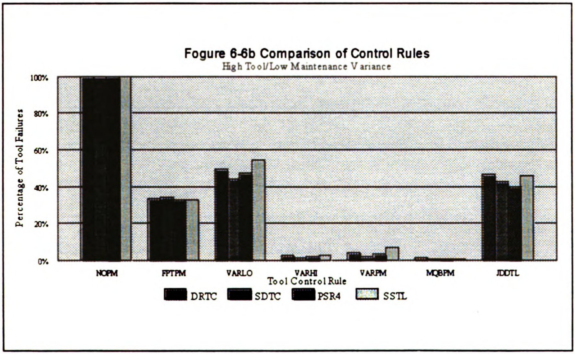

Fogure 6-6b Comparison of Control Rules
High Tool/Low Maintenance Variance
Percentage of Tool Failures
100%
80%
60%
40%
20%
0%
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rule
DRTC
SDTC
PSR4
SSTL

Figure 6-6c Comparison of Control Rules

Low Tool/High Maintenance Variance

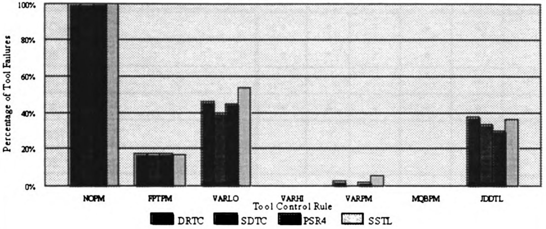


Figure 6-6d Comparison of Control Rules

High Tool/High Maintenance Variance

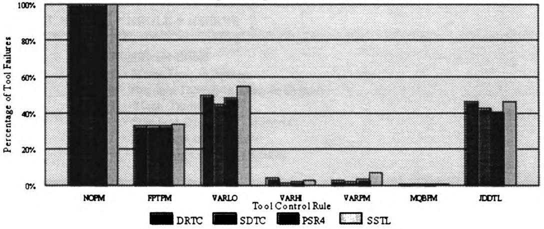


Table 6-13 Synopsis of ANOVA Results from Analysis of Effects

SOURCE OF VARIATION	TSY	STS	TRD	STD	PLT	PCM
NBATCH	*	*	*	*	*	*
MTOOL	*	*	*	*	*	*
NLIFE					*	*
NRULE	*	*	*	*	*	*
NSERVE						
MTOOL * NLIFE	*				*	*
MTOOL * NRULE	*	*	*	*	*	*
MTOOL * NSERVE						
NLIFE * NRULE						
NLIFE * NSERVE						
NRULE * NSERVE						
MTOOL * NLIFE * NRULE						
MTOOL * NRULE * NSERVE						
NLIFE * NRULE * NSERVE						
MTOOL * NLIFE * NSERVE						
MTOOL * NLIFE * NRULE * NSERVE						

Legend: * - Significant Effect
TSY - Mean Time in System
STS - Standard Deviation Time in System
TRD - Mean Tardiness
STD - Standard Deviation Tardiness
PLT - Percentage of Jobs Late
PCM - Percentage of Tool Failures

- The main effects of tool life variance (NLIFE) is significant for performance measures dealing with percentage of jobs late and percentage of tool failures.

- The higher order interaction between tool control rules (MTOOL) and tool life variance (NLIFE) is significant for mean time in system, percentage of jobs late, and percentage of tool failures.

- All other main effects and interactions are not significant. This includes all three and four way interactions.

An analysis of these effects for the performance measures allow a number of conclusions and observations to be made. These conclusions include:

- Tool control rules which allow variable PM perform better than others, particularly PM rules which promote early maintenance prior to the PM point.

- Job priority rules which are due date based (DRTC and PSR4) perform better than sequence dependent rules (SDTC and SSTL). This is attributed to the fact that due date rules evaluate all jobs in queue every time a job is done processing or tool failure occurs. By prioritizing all jobs in queue, a more efficient evaluation of jobs in queue is made.

- Maintenance service time (NSERVE) does not significantly influence shop performance. The reason is that maintenance utilization is too low to cause delays in tool repair. Higher maintenance utilization would cause maintenance queue to increase resulting in longer delays and lower tool availability. Increasing mean service time would likely change this result.

- Tool life variance (NLIFE) is only significant for two out of six performance measures. While this result may seem surprising, the reason can be attributed to tool availability. Availability can be viewed as the time the tool is not in maintenance (down time). On average, a tool is in maintenance 3 hours for every

100 hours of processing time (3% down time) based on a preventive maintenance (PM) heuristic. In the worst case scenario, that of corrective maintenance (CM), down time occurs on average 6 hours for every 120 hours of processing time (5%). Should tool availability decrease substantially, this factor would become significant. In general, the influence of NSERVE and NLIFE on the shop performance measures is not very strong. This indicates that the control rules (MTOOL and NRULE) are the main decision rules that affect shop performance. However, if the means are large, NSERVE and NLIFE can also affect shop performance.

- The best combination of rules consisted of: PSR4-MQBPM, PSR4-VARHI, DRTC-MQBPM and DRTC-VARHI. This is attributed to the fact that PSR4 and DRTC, and MQBPM and VARHI are consistently the better performing job priority rules and tool control rules respectively.

6.3 A PRIORI HYPOTHESES ANALYSIS

When higher order interactions are significant, as indicated in the ANOVA analysis, interpretation of linear contrasts may not be valid. One Way ANOVA is used when comparing two treatment means. Also used, is multiple comparison (Tukey HSD) to analyze a priori hypotheses (Neter et al., 1990). This involves comparing appropriate treatment means as discussed in Chapter 5. The use of Tukey multiple comparison will show which treatments, if any, are significantly different. With significant higher order interaction between job priority rules (NRULE) and tool control rules (MTOOL), multiple comparisons of job rules for each tool rule and comparison of tool rules for each job rules is necessary. It should be noted that the significant higher order interaction between tool rules (MTOOL) and tool life (NLIFE) did not alter the rank order significant groups for the multiple comparison.

6.3.1 Hypothesis 1

Hypothesis 1 tests whether sequence dependant job priority rules used to select the next group of jobs is affected by the decision to use job due date or tool condition information. When replacing a tool on a machine, is it better to select the next tool based on job due date (SDTC) the tool which can be utilized the longest on the machine (SSTL). The objective is to fully utilize the advantages of sequence dependency which reduces setup time.

In summary, there is no difference between sequencing dependant rules, accept the null hypothesis. The results of Tables 6-14(a-g) and Table 6-15 show that for any of the performance measures, there is a significant difference between SDTC and SSTL. This holds for all six performance measures. Examining Tables 6-14(a-g) and Figures 6-7(a-f), it can be seen that the rank order shows SDTC performs slightly better than SSTL on every measure. The results show that there is no significant difference between using due date or tool condition information when selecting the next tool for a machine.

6.3.2 Hypothesis 2

Hypothesis 2 continues the examination of job priority rules by examining the

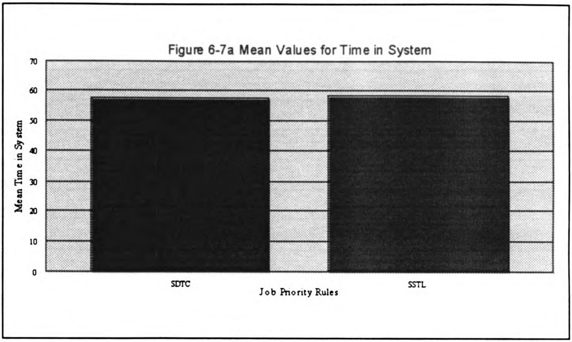


Figure 6-7a Mean Values for Time in System
70
60
50
40
30
20
10
0
Mean Time in System
SDTC
SSTL
Job Priority Rules

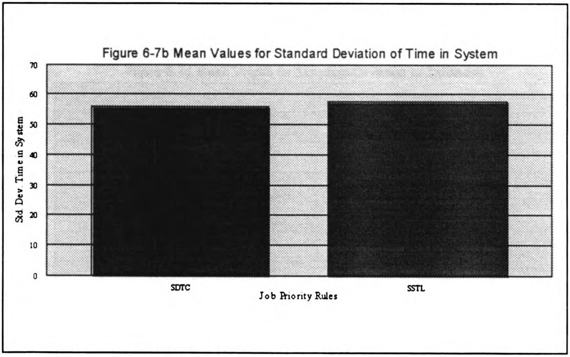


Figure 6-7b Mean Values for Standard Deviation of Time in System
70
60
50
40
30
20
10
0
Std Dev. Time in System
SDTC
SSTL
Job Priority Rules

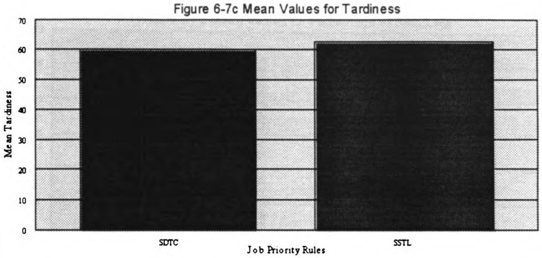


Figure 6-7c Mean Values for Tardiness
Mean Tardiness
70
60
50
40
30
20
10
0
SDTC
SSTL
Job Priority Rules

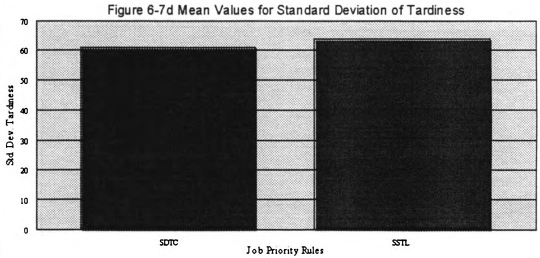


Figure 6-7d Mean Values for Standard Deviation of Tardiness
Std Dev. Tardiness
70
60
50
40
30
20
10
0
SDTC
SSTL
Job Priority Rules

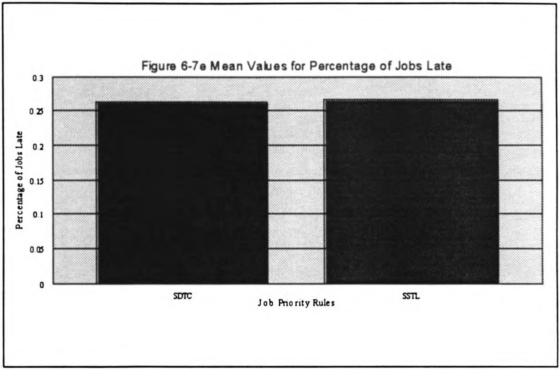


Figure 6-7e Mean Values for Percentage of Jobs Late
Percentage of Jobs Late
0.3
0.25
0.2
0.15
0.1
0.05
0
SDTC
SSTL
Job Priority Rules

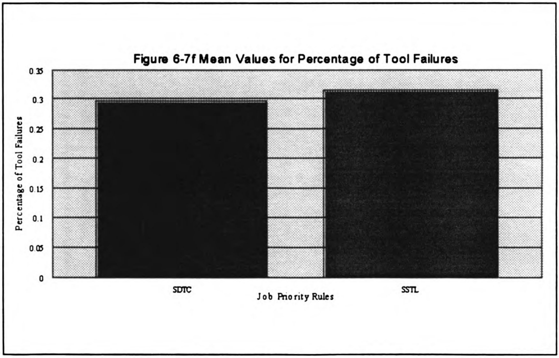


Figure 6-7f Mean Values for Percentage of Tool Failures
Percentage of Tool Failures
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
SDTC
SSTL
Job Priority Rules

Table 6-14a Tukey Multiple Comparisons of Job Priority Rules for NOPM Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	PSR4	PSR4	PSR4	SDTC	SDTC
DRTC	DRTC	DRTC	DRTC	SSTL	PSR4
SDTC	SDTC	SDTC	SDTC	DRTC	SSTL
SSTL	SSTL	SSTL	SSTL	PSR4	DRTC

Table 6-14b Tukey Multiple Comparisons of Job Priority Rules for FPTPM Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	PSR4	PSR4	PSR4	SDTC	PSR4
DRTC	DRTC	DRTC	DRTC	SSTL	SDTC
SDTC	SDTC	SDTC	SDTC	DRTC	SSTL
SSTL	SSTL	SSTL	SSTL	PSR4	DRTC

Table 6-14c Tukey Multiple Comparisons of Job Priority Rules for VARLO Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	PSR4	PSR4	DRTC	SDTC	SDTC
DRTC	DRTC	DRTC	PSR4	SSTL	PSR4
SDTC	SDTC	SDTC	SDTC	DRTC	DRTC
SSTL	SSTL	SSTL	SSTL	PSR4	SSTL

Table 6-14d Tukey Multiple Comparisons of Job Priority Rules for VARHI Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	DRTC	PSR4	DRTC	SDTC	SDTC
DRTC	PSR4	DRTC	PSR4	SSTL	PSR4
SDTC	SDTC	SDTC	SDTC	DRTC	SSTL
SSTL	SSTL	SSTL	SSTL	PSR4	DRTC

Table 6-14e Tukey Multiple Comparisons of Job Priority Rules for VARPM Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	PSR4	PSR4	DRTC	SDTC	SDTC
DRTC	DRTC	DRTC	PSR4	SSTL	PSR4
SDTC	SDTC	SDTC	SDTC	DRTC	DRTC
SSTL	SSTL	SSTL	SSTL	PSR4	SSTL

Table 6-14f Tukey Multiple Comparisons of Job Priority Rules for MQBPM Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4	PSR4	PSR4	PSR4	SDTC	SDTC
DRTC	DRTC	DRTC	DRTC	SSTL	PSR4
SDTC	SDTC	SDTC	SDTC	DRTC	SSTL
SSTL	SSTL	SSTL	SSTL	PSR4	DRTC

Table 6-14g Tukey Multiple Comparisons of Job Priority Rules for JDDTL Tool Rule.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4 DRTC SDTC SSTL	PSR4 DRTC SDTC SSTL	PSR4 DRTC SDTC SSTL	PSR4 DRTC SDTC SSTL	SDTC SSTL DRTC PSR4	PSR4 SDTC SSTL DRTC

Table 6-15 Analysis of Variance for Sequence Dependent Job Priority Rules SDTC and SSTL.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
3.397 (.337)	1.419 (.234)	2.198 (.139)	1.221 (.269)	.445 (.505)	1.141 (.286)

Legend: * - indicates significant difference

differences between the first three rules: DRTC, PSR4, and SDTC. The analysis of these three rules allow a comparison of different job due date based rules. This differs from the job priority rule SSTL which used tool load as a criteria for selection and not due date.

For Hypothesis 2, the null is rejected because there is a significant difference between the three job priority rules. Tables 6-14(a-g) and Figures 6-8(a-f) show that rules PSR4 and DRTC are significantly different for most performance measure. For mean time in system, there is no significant difference between the three rules. As for standard deviation of time in system and standard deviation of tardiness, PSR4 and DRTC are both significantly different than SDTC, but are not significantly different than each other. For mean tardiness and percentage of jobs late, all three job rules are significantly different from each other (in most cases). For mean tardiness, PSR4 is the best performing rule followed by DRTC and the SDTC (Figure 6-8c), whereas, the opposite ranking is observed for percentage of jobs late (Figure 6-8d). The log percentage of tool failures shows that SDTC and PSR4 are significantly different than DRTC (except for NOPM tool rule), but are not significantly different than each other.

Figures 6-8(a-d) show that PSR4 is the best performing job priority rule, followed by DRTC and SDTC respectively. In Figure 6-8e, the rank order is reversed with PSR4 being the worst performer. Only in log percentage of tool failures (Figure 6-8f) does the order of the job rules change where SDTC is first, followed by PSR4 and then DRTC in performance (except under FPTPM tool rule).

Figure 6-8a Mean Values for Time in System

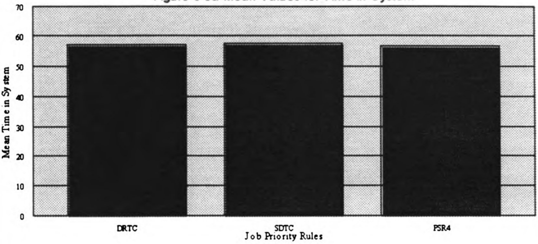
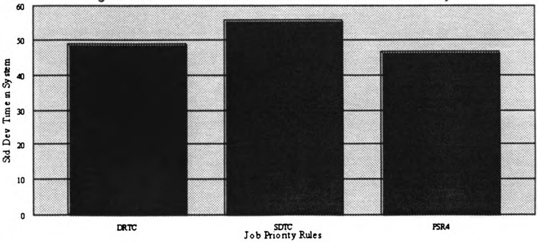


Figure 6-8b Mean Values for Standard Deviation of Time in System



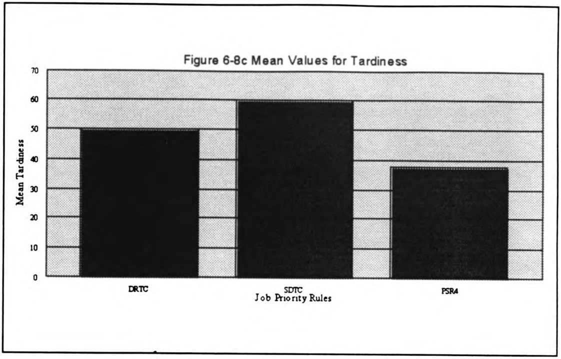


Figure 6-8c Mean Values for Tardiness
Mean Tardiness
0
10
20
30
40
50
60
70
DRTC
SDTC
PSR4
Job Priority Rules

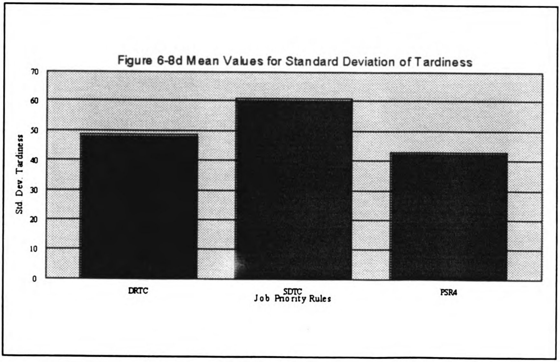


Figure 6-8d Mean Values for Standard Deviation of Tardiness
Std. Dev. Tardiness
0
10
20
30
40
50
60
70
DRTC
SDTC
PSR4
Job Priority Rules

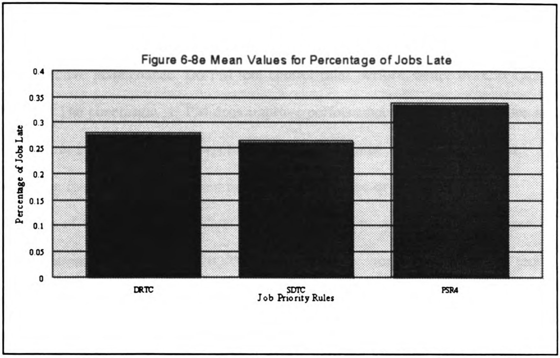


Figure 6-8e Mean Values for Percentage of Jobs Late
Percentage of Jobs Late
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
DRTC
SDTC
PSR4
Job Priority Rules

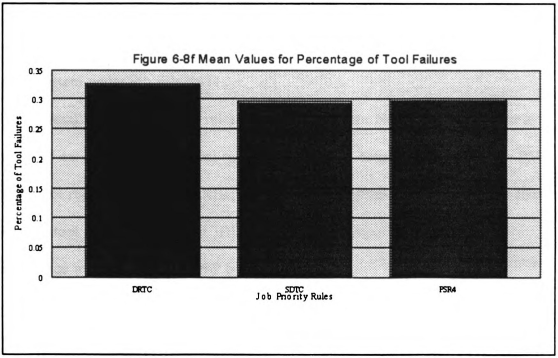


Figure 6-8f Mean Values for Percentage of Tool Failures
Percentage of Tool Failures
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
DRTC
SDTC
PSR4
Job Priority Rules

6.3.3 Hypothesis 3

Hypothesis 3 tests whether there is any benefit to preventative maintenance over corrective maintenance. Do PM tool control rules perform better the CM rule (NOPM)? The conclusion is, PM does improve performance significantly (Tables 6-16 a-d), thus rejecting the null hypothesis. The rule NOPM is usually the worst performing tool rule for mean time in system, percentage of jobs late, and log percentage of tool failures. For standard deviation time in system, mean tardiness, standard deviation of tardiness, NOPM is a significantly worse performer than tool rules VARLO, VARHI, VARPM, and MQBPM (in most cases). The PM tool rules, FPTPM and JDDTL, perform significantly worse than NOPM for mean and standard deviation of tardiness. JDDTL performed significantly worse than NOPM for standard deviation of time in system. While there is no significant difference between NOPM and FPTPM, NOPM is only ranked lower for standard deviation of time in system under job rule SSTL.

Overall, PM tool control rules perform better than NOPM, but there are a number of exceptions. NOPM tool rule never performs better than the variable PM tool control rules: VARPM, VARHI, and MQBPM (Figures 6-9 a-f). The two fixed PM point tool rules: FPTPM and JDDTL, performed worse on half of the performance measures (Figures 6-9 b-d).

6.3.4 Hypothesis 4

Hypothesis 4 answers whether a fixed PM policy is better than a variable PM

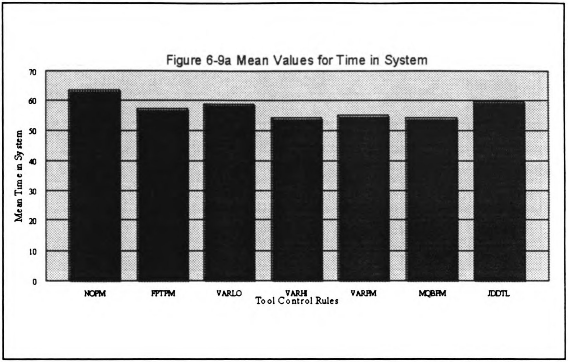


Figure 6-9a Mean Values for Time in System
Mean Time in System
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules

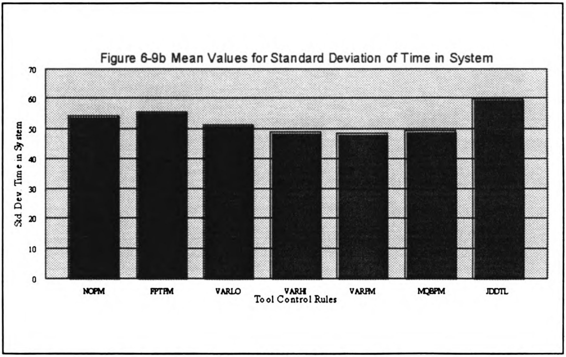


Figure 6-9b Mean Values for Standard Deviation of Time in System
Std Dev Time in System
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules

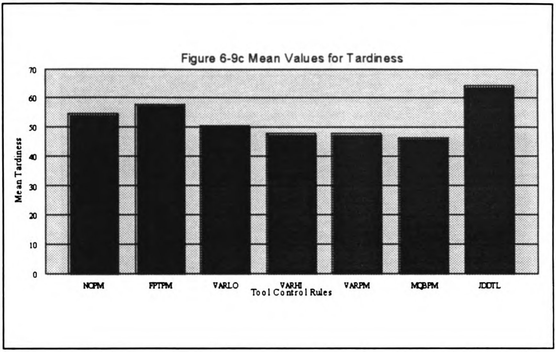


Figure 6-9c Mean Values for Tardiness
Mean Tardiness
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules

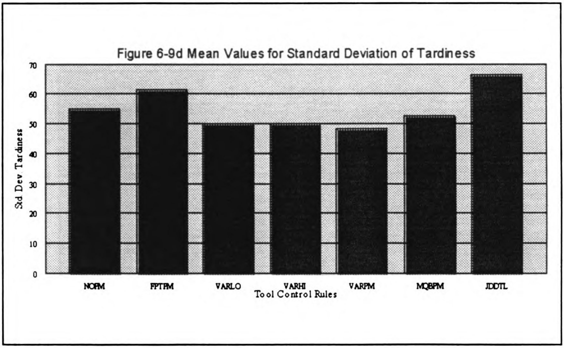


Figure 6-9d Mean Values for Standard Deviation of Tardiness
Std Dev Tardiness
70
60
50
40
30
20
10
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules

Figure 6-9e Mean Values for Percentage of Jobs Late

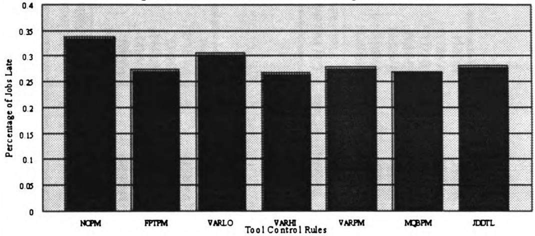


Figure 6-9f Mean Values for Percentage of Tool Failures

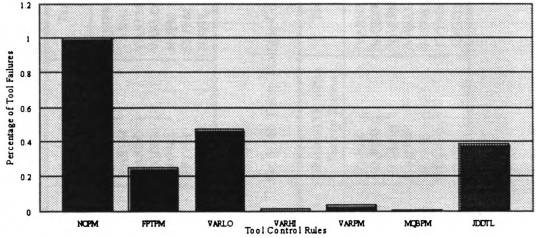


Table 6-16a Tukey Multiple Comparisons of Tool Control Rules for DRTC Job Rule.

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
MQBPM	VARHI	MQBPM	VARHI	VARHI	MQBPM
VARHI	VARPM	VARHI	VARPM	MQBPM	VARHI
VARPM	VARLO	VARPM	VARLO	FPTPM	VARPM
FPTPM	MQBPM	VARLO	MQBPM	JDDTL	FPTPM
VARLO	NOPM	NOPM	NOPM	VARPM	JDDTL
JDDTL	FPTPM	FPTPM	FPTPM	VARLO	VARLO
NOPM	JDDTL	JDDTL	JDDTL	NOPM	NOPM

Table 6-16b Tukey Multiple Comparisons of Tool Control Rules for SDTC Job Rule.

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
MQBPM	VARHI	VARHI	VARHI	MQBPM	MQBPM
VARHI	VARPM	MQBPM	VARPM	VARHI	VARHI
VARPM	MQBPM	VARPM	MQBPM	FPTPM	VARPM
FPTPM	VARLO	VARLO	VARLO	VARPM	FPTPM
VARLO	NOPM	NOPM	NOPM	JDDTL	JDDTL
JDDTL	FPTPM	FPTPM	FPTPM	VARLO	VARLO
NOPM	JDDTL	JDDTL	JDDTL	NOPM	NOPM

Table 6-16c Tukey Multiple Comparisons of Tool Control Rules for PSR4 Job Rule.

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
MQBPM	VARHI	MQBPM	VARHI	MQBPM	MQBPM
VARHI	MQBPM	VARHI	MQBPM	VARHI	VARHI
VARPM	VARPM	VARPM	VARPM	VARPM	VARPM
FPTPM	VARLO	FPTPM	NOPM	FPTPM	FPTPM
VARLO	NOPM	VARLO	FPTPM	JDDTL	JDDTL
JDDTL	FPTPM	NOPM	VARLO	VARLO	VARLO
NOPM	JDDTL	JDDTL	JDDTL	NOPM	NOPM

Table 6-16d Tukey Multiple Comparisons of Tool Control Rules for SSTL Job Rule.

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
MQBPM	VARPM	MQBPM	VARPM	VARHI	MQBPM
VARHI	MQBPM	VARPM	MQBPM	MQBPM	VARHI
VARPM	VARHI	VARHI	VARHI	FPTPM	VARPM
FPTPM	VARLO	VARLO	VARLO	VARPM	FPTPM
VARLO	FPTPM	NOPM	FPTPM	JDDTL	JDDTL
JDDTL	NOPM	FPTPM	NOPM	VARLO	VARLO
NOPM	JDDTL	JDDTL	JDDTL	NOPM	NOPM

policy. This test requires the comparison of three variable PM tool control rules: VARLO, VARHI, and VARPM, to the fixed PM rule FPTPM.

FPTPM rules were significantly different than the variable PM rules (Tables 6-16 a-d) except for percentage of jobs late. Tool control rule VARHI performed significantly better than FPTPM for all measures except percentage of jobs late and tardiness (when using PSR4 job rule). For this performance measure (Figures 6-10 a-f), VARHI is not significantly different but does perform better (Figure 6-10c). FPTPM performs significantly worse than any variable PM tool rule for standard deviation of time in system, and mean and standard deviation of tardiness. The exception to this is when job priority rule PSR4 is used. FPTPM tool rule performs significantly better than variable PM rule VARLO for mean time in system, log percentage of tool failures, and percentage of jobs late. FPTPM tool rule performed significantly worse than VARPM for all performance measures except percentage of jobs late. For this measure, FPTPM outperforms VARPM (Figure 6-10c).

The results show that variable PM rules outperform fixed point PM rules. The PM tool rules, VARHI and VARPM consistently outperformed FPTPM. These two PM tool rules allow for early PM. The third PM tool rule, VARLO, allows PM to be postponed past the PM point causing more tool failures (Figure 6-10f). This explains why VARLO performs worse than FPTPM three of six performance measures (Figures 6-10 b-d).

Figure 6-10a Mean Values for Time in System

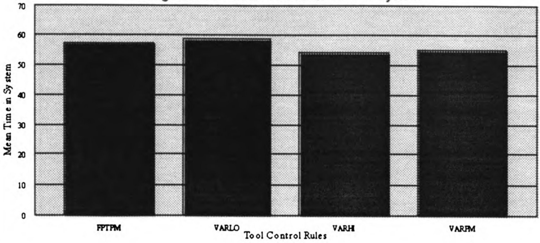
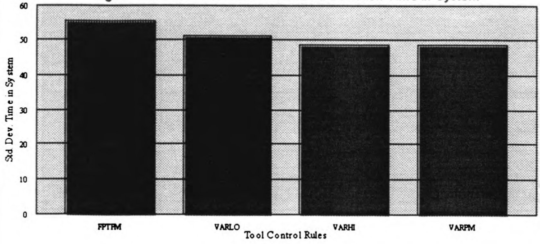


Figure 6-10b Mean Values for Standard Deviation Time in System



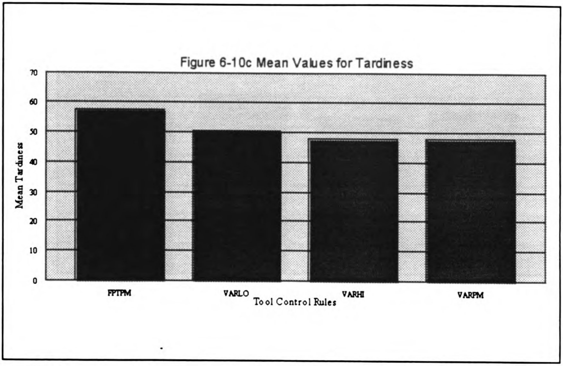


Figure 6-10c Mean Values for Tardiness
Mean Tardiness
70
60
50
40
30
20
10
0
FPTPM
VARLO
VARHI
VARPM
Tool Control Rules

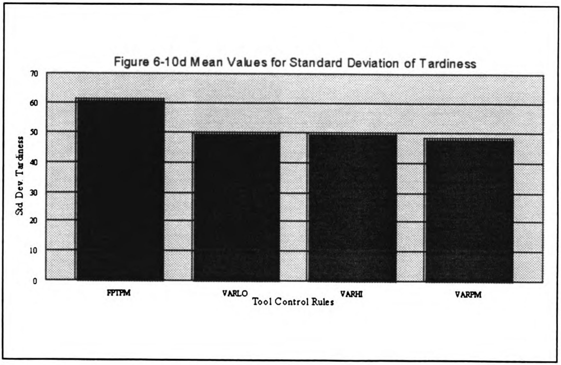


Figure 6-10d Mean Values for Standard Deviation of Tardiness
Std Dev. Tardiness
70
60
50
40
30
20
10
0
FPTPM
VARLO
VARHI
VARPM
Tool Control Rules

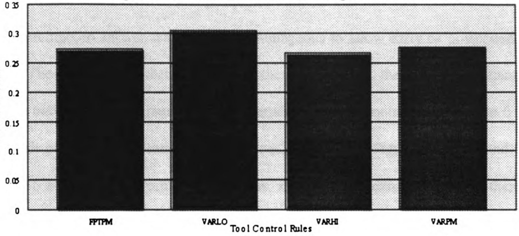


Figure 6-10e Mean Values for Percentage of Jobs Late

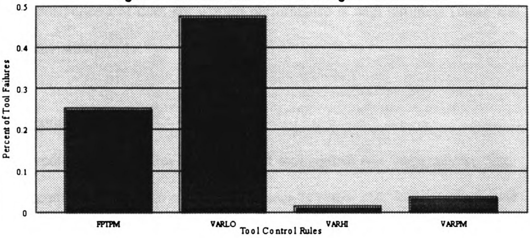


Figure 6-10f Mean Values for Percentage of Tool Failures

6.3.5 Hypothesis 5

Hypothesis 5 tests whether there is a significant difference between early variable PM tool rule (VARHI) and postponed variable PM tool rule (VARLO). The question attempts to answer whether it is advantageous to allow early or postponed tool PM. The results show that the null hypothesis is rejected, there is a significant difference between early versus postponed variable PM tool control rules (Table 6-17). For all performance measures, VARHI performs better (Figures 6-11 a-f and Tables 6-16 a-d). Only performance measures, mean and standard deviation is there no significant differences between VARHI and VARLO tool rules (Table 6-17). While these two measures are not significantly different, VARHI still outperforms VARLO (Figure 6-10 c-d).

VARHI performs better than VARLO because of the lower percentage of tool failures. This shows that early PM is preferred to that of postponed PM. The only time that postponed PM does not worsen performance is with tardiness (mean and standard deviation).

6.3.6 Hypothesis 6

Hypothesis 6 compares a variable PM tool control rule which allows both early or postponed PM when maintenance queue is empty (MQBPM) with that of variable PM (VARPM). The null hypothesis tests whether there is a significant difference between tool rules which considers maintenance queues versus a tool rule that does not.

Table 6-17 Analysis of Variance for Early and Postponed Variable PM Tool Control Rules.

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
15.128 (.000)*	3.268 (.042)*	2.331 (.128)	.331 (.566)	10.647 (.001)*	487.533 (000)*

Legend: * - indicates significant difference

Table 6-18 Analysis of Variance for Variable PM Tool Control Rules With Maintenance Queue Information (MQBPM) and Without (VARPM).

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
1.031 (.311)	2.917 (.045)*	6.026 (.300)	.551 (.458)	3.456 (.046)*	126.598 (.000)*

Legend: * - indicates significant difference

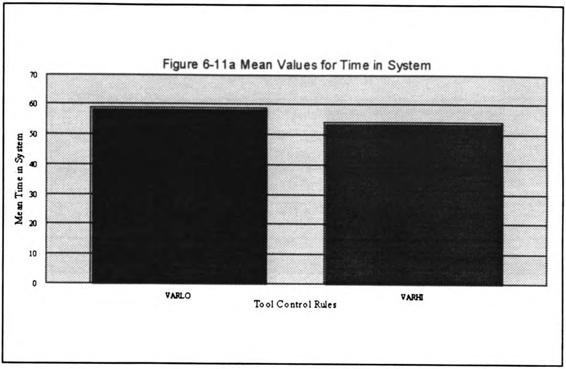


Figure 6-11a Mean Values for Time in System
70
60
50
40
30
20
10
0
Mean Time in System
VARLO
VARHI
Tool Control Rules

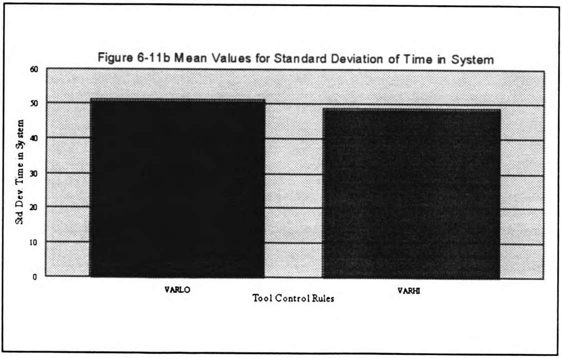


Figure 6-11b Mean Values for Standard Deviation of Time in System
60
50
40
30
20
10
0
Std Dev. Time in System
VARLO
VARHI
Tool Control Rules

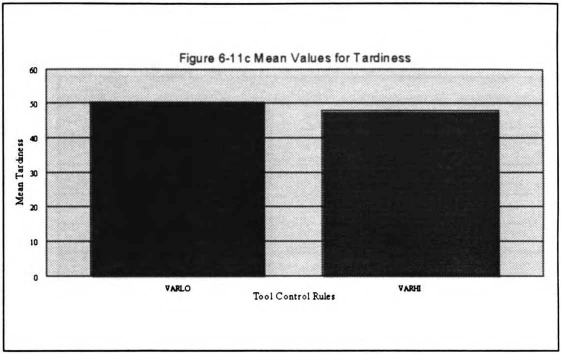


Figure 6-11c Mean Values for Tardiness
Mean Tardiness
60
50
40
30
20
10
0
VARLO
VARHI
Tool Control Rules

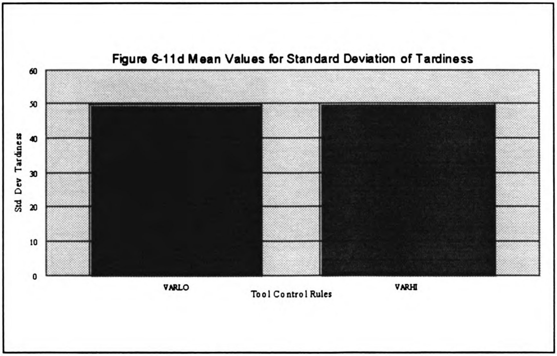
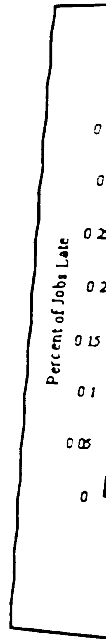


Figure 6-11d Mean Values for Standard Deviation of Tardiness
Std Dev Tardiness
60
50
40
30
20
10
0
VARLO
VARHI
Tool Control Rules


Percent of Jobs Late
0 15
0 1
0 05
0

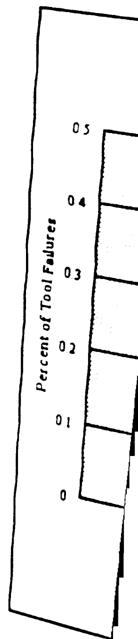

Percent of Tool Failures
0 5
0 4
0 3
0 2
0 1
0

Figure 6-11e Mean Values for Percentageof Jobs Late

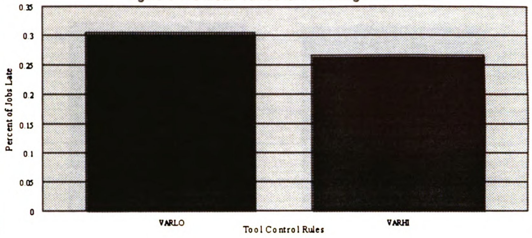


Figure 6-11f Mean Values for Percentageof Tool Failures

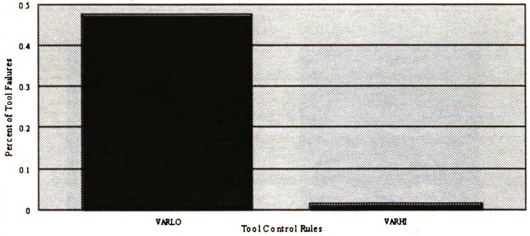


Figure 6-12a Mean Values for Time in System

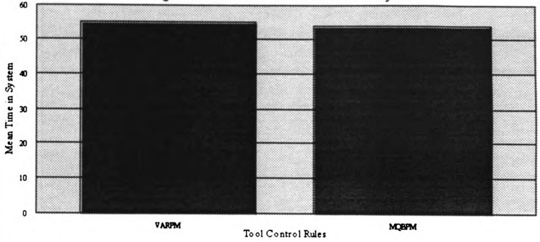
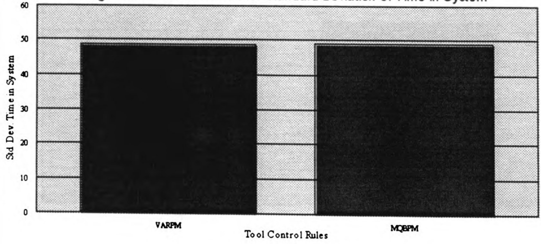


Figure 6-12b Mean Values for Standard Deviation of Time in System



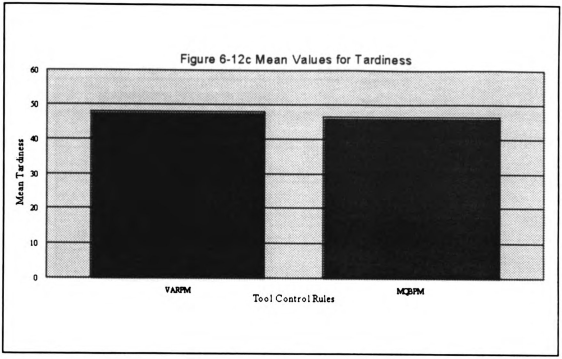


Figure 6-12c Mean Values for Tardiness
Mean Tardiness
60
50
40
30
20
10
0
VARPM
MQBPM
Tool Control Rules

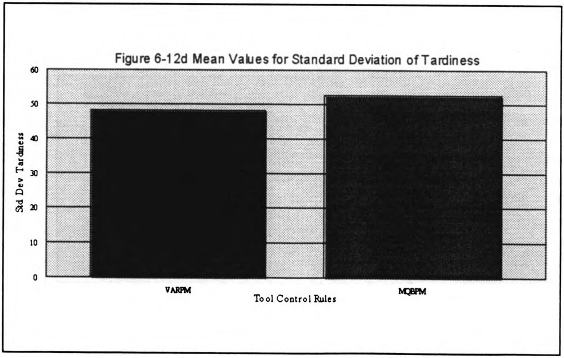


Figure 6-12d Mean Values for Standard Deviation of Tardiness
Std Dev Tardiness
60
50
40
30
20
10
0
VARPM
MQBPM
Tool Control Rules

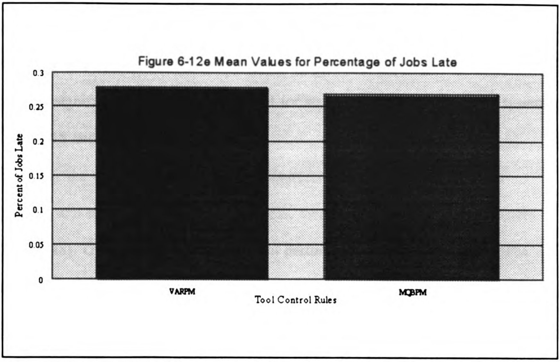


Figure 6-12e Mean Values for Percentage of Jobs Late
Percent of Jobs Late
0.3
0.25
0.2
0.15
0.1
0.05
0
VARPM
MQBPM
Tool Control Rules

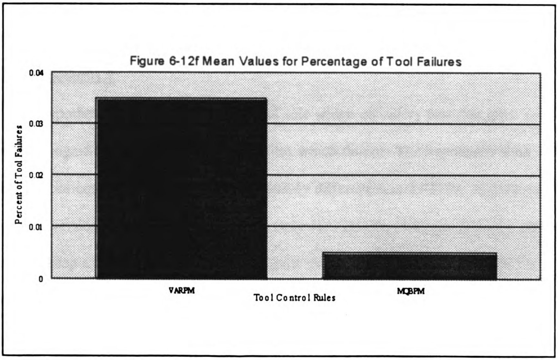


Figure 6-12f Mean Values for Percentage of Tool Failures
Percent of Tool Failures
0.04
0.03
0.02
0.01
0
VARPM
MQBPM
Tool Control Rules

The null hypothesis is rejected, there is a significant difference between VARPM and MQBPM. MQBPM performs significantly better than VARPM for percentage of jobs late and log percentage of tool failures (Table 6-18). VARPM performs significantly better than MQBPM for standard deviation of time in system (Table 6-18 and Figure 6-12b).

For the next three performance measures, mean time in system, mean tardiness, and standard deviation of tardiness, there was no significant differences (Table 6-18). Of these three non-significant performance measures, the MQBPM rule performed best for mean time in system and mean tardiness (Figure 6-12 b-c). For standard deviation of tardiness, VARPM performs better than MQBPM for the two measures of variance, standard deviation of time in system and tardiness. While VARPM causes less variation, it performs worse on all other measures.

6.3.7 Hypothesis 7

Hypothesis 7 looks at whether a tool rule which considers past due jobs performs significantly different than PM rules which do not. The hypothesis tests whether tool control rule JDDTL is significantly different than FPTPM. JDDTL is a modified version of the tool rule FPTPM. Only JDDTL considers job due date status and will keep a tool in production until all past due jobs are processed or until the tool fails.

The null hypothesis is rejected, there is a significant difference between the two tool control rules (FPTPM and JDDTL). FPTPM performs significantly better than JDDTL for all performance measures except standard deviation of tardiness and percentage of jobs late (Table 6-19). While FPTPM did not perform significantly different than JDDTL, FPTPM still outperformed JDDTL for both standard deviation of tardiness and percentage of jobs late (Figure 6-13e).

The poor performance of JDDTL can be contributed to the greater percentage of tool failures. The fact that JDDTL continues processing past due jobs causes the risk (and number) of tool failures to rise. The added risk is only incurred for past due jobs.

The conclusion is, using job due date as a means of tool control is not beneficial. Allowing past due jobs the ability to keep a tool in production in excess of its PM point does not improve shop performance. The additional risk of tool failure outweighs the benefit of job completion.

6.3.8 Hypothesis 8

Hypothesis 8 examines whether tool life variance effects the performance of the shop. The null hypothesis tests whether there is a significant difference between LOW and HIGH tool life variance. Only performance measures, percentage of jobs late and log percentage of tool failures performance, are significantly influenced by tool life variance (Table 6-20). The logic that tool life variance has a significant effect on percentage of tool failures is apparent (Figures 6-14 a-f). What is surprising is the limited effect tool life had on mean and standard deviation of tardiness and time in system. The explanation relates to the amount of lost tool

Table 6-19 Analysis of Variance for Fixed PM Point Tool Control Rules Which Considers Job Due Date (JDDTL) and Does Not (FPTPM).

Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
3.997 (.036)*	4.621 (.032)*	6.310 (.013)*	3.496 (.071)	.375 (.540)	215.917 (000)*

Legend: * - indicates significant difference

Figure 6-13a Mean Values for Time in System

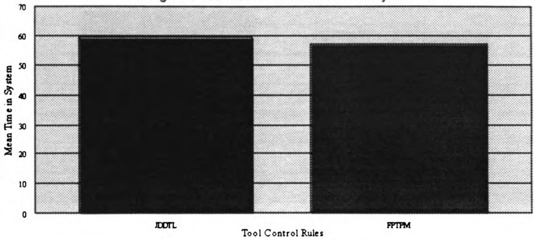


Figure 6-13b Mean Values for Standard Deviation of Time in System

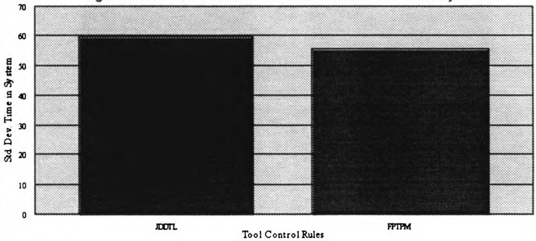


Figure 6-13c Mean Values for Tardiness

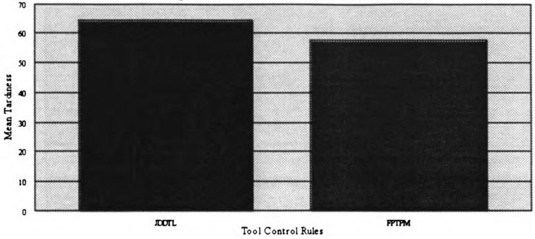
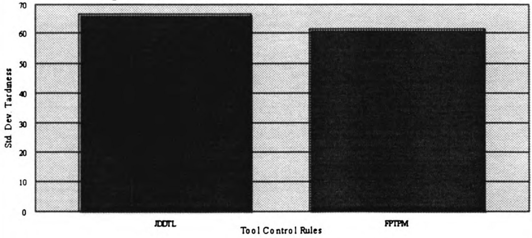


Figure 6-13d Mean Values for Standard Deviation of Tardiness



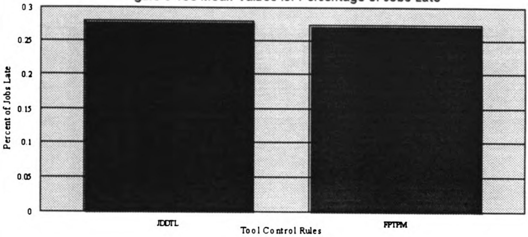


Figure 6-13e Mean Values for Percentage of Jobs Late

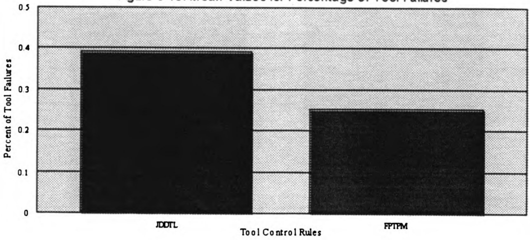


Figure 6-13f Mean Values for Percentage of Tool Failures

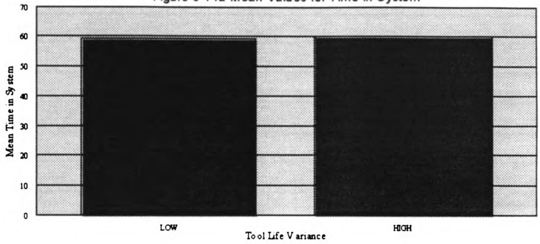


Figure 6-14a Mean Values for Time in System

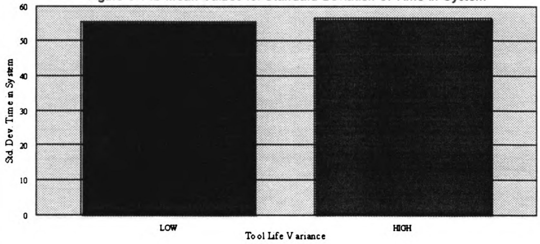


Figure 6-14b Mean Values for Standard Deviation of Time in System

Figure 6-14c Mean Values for Tardiness

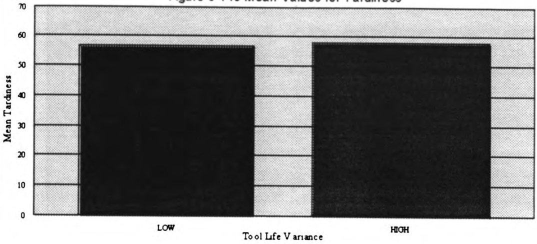


Figure 6-14d Mean Values for Standard Deviation of Tardiness

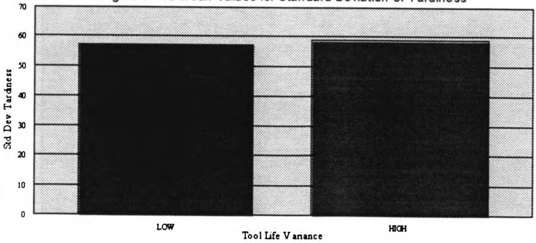


Figure 6-14e Mean Values for Percentage of Jobs Late

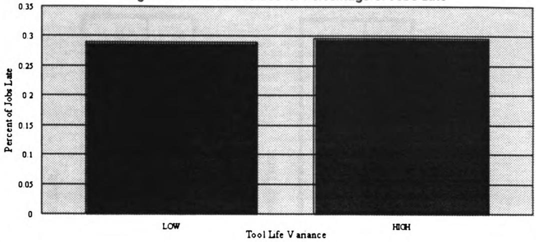


Figure 6-14f Mean Values for Percentage of Tool Failures

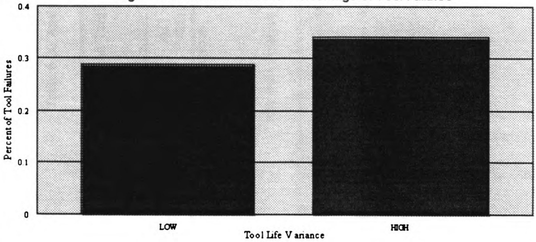


Table 6-20 Analysis of Variance for Tool Life Variance.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
1.058 (.304)	.901 (.343)	.627 (.428)	1.165 (.281)	1.720 (.121)	5.410 (.020)*

Legend: * - indicates significant difference

Table 6-21 Analysis of Variance for Maintenance Service Time.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
.611 (.918)	.811 (.776)	.209 (.647)	.111 (.739)	.026 (.871)	.001 (.995)

Legend: * - indicates significant difference

availability which is not impacted significantly by tool life variance.

6.3.9 Hypothesis 9

Hypothesis 9 is similar to Hypothesis 8 but looks at how maintenance service time variance effects shop performance. The hypothesis tests whether there is a significant difference between LOW and HIGH maintenance time variance. The null hypothesis is accepted, there is no significant difference for all six performance measures (Table 6-21). Figures 6-15 (a-f) clearly show that each performance measure has nearly identical results under both LOW and HIGH maintenance variance. The unexpected result can be contributed to the low utilization of the maintenance process (ranging from 11% to 22%). With a low utilization rate, the maintenance queue waiting time is minimal, resulting in less loss tool availability is higher. Should maintenance variance increase or frequency of tool failure increase, maintenance utilization would increase causing increased queue delay. Only when utilization exceeds 60% would maintenance variance become a significant factor. The problem with this utilization rate is that it would not emulate the visited shop floors.

6.3.10 Research Hypotheses Summary

A summary of the hypothesis results are provided in Table 6-22. The results show that of the tool control rules, MQBPM and VARPM, consistently provide the best performance. The most consistent performer for the job priority rules is PSR4,

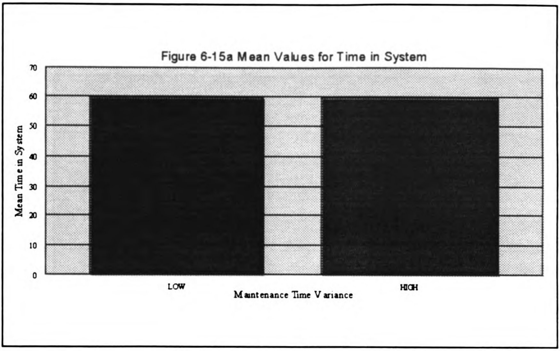


Figure 6-15a Mean Values for Time in System
Mean Time in System
70
60
50
40
30
20
10
0
LOW
HIGH
Maintenance Time Variance

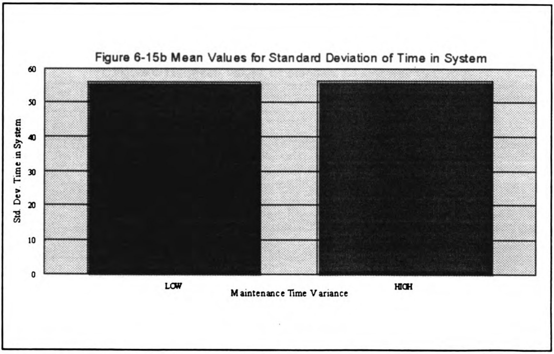


Figure 6-15b Mean Values for Standard Deviation of Time in System
Std. Dev. Time in System
60
50
40
30
20
10
0
LOW
HIGH
Maintenance Time Variance

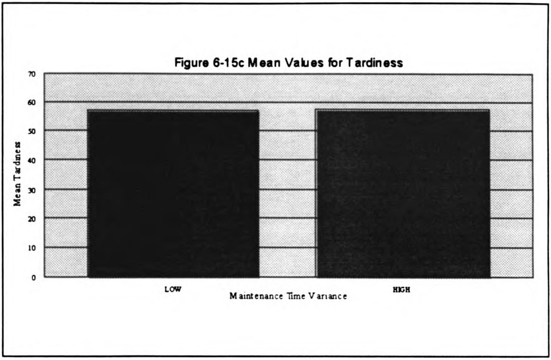


Figure 6-15c Mean Values for Tardiness
70
60
50
40
30
20
10
0
Mean Tardiness
LOW
HIGH
Maintenance Time Variance

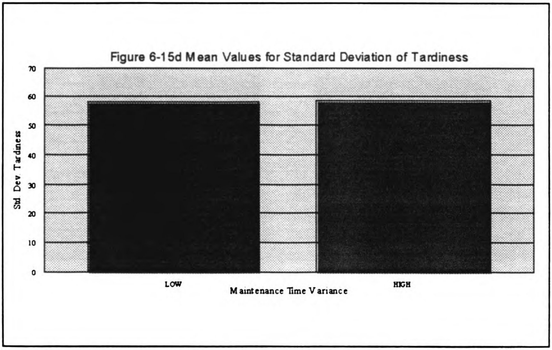


Figure 6-15d Mean Values for Standard Deviation of Tardiness
70
60
50
40
30
20
10
0
Std. Dev. Tardiness
LOW
HIGH
Maintenance Time Variance

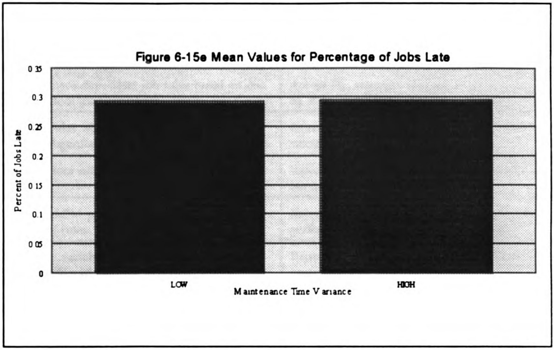


Figure 6-15e Mean Values for Percentage of Jobs Late
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Percent of Jobs Late
LOW
HIGH
Maintenance Time Variance

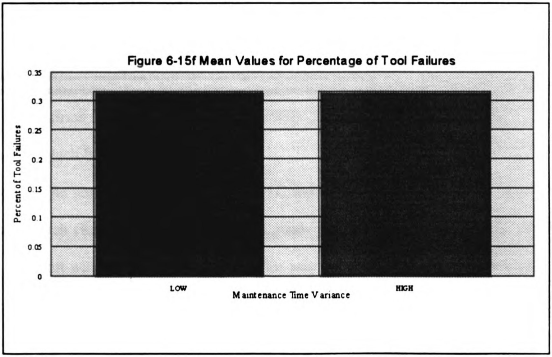


Figure 6-15f Mean Values for Percentage of Tool Failures
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Percent of Tool Failures
LOW
HIGH
Maintenance Time Variance

Table 6-22 Summary of Hypothesis Results

Hypotheses	Conclusion
1. Sequence dependent job rules based on due date or tool load are equal.	Accept H_0, sequence dependent job rule based on due date perform only slightly better.
2. Job rules which prioritize by due date are equal, regardless of additional information.	Reject H_0, only certain forms of information enhances performance not.
3. CM tool rule is equal to PM tool rules.	Reject H_0, most PM tool rules perform better, but not all.
4. Fixed PM point tool rules equals variable PM tool rules.	Reject H_0, variable PM rules with early PM perform better than fixed PM point rules.
5. Early variable PM tool rule equals postponed variable PM tool rules.	Reject H_0, early PM performs better than postponed PM tool rule.
6. Variable PM tool rule which does and does not consider maintenance queue information are equal.	Reject H_0, using maintenance queue in variable PM rule improves performance.
7. Fixed PM point tool rule equals fixed PM point tool rules which considers past due jobs.	Reject H_0, considering past due jobs decreases performance for fixed PM point rule.
8. Tool life variance does not impact shop performance.	Accept H_0.
9. Maintenance service variance does not impact performance.	Accept H_0.

which confirms finding by Melnyk et al. (1989). Specific results found in the analysis which bare mentioning include:

- The sequence dependent rules SDTC and SSTL, while showing promise in past research (Kannan and Lyman, 1992; Lyman, 1993), fail to benefit an environment with stochastic life tooling. This may be attributed to the fact that the ratio of setup time to processing time is 20%. Higher levels of this ratio are likely to change these findings.

- The due date rule PSR4 which utilizes sequence dependency while considering job slack, performs best. The job rule DRTC, which looks at job due date when prioritizing, performs second best. The results show that while sequence dependency can reduce the number of tool changes, job due date is more important to shop performance. This outcome is most apparent in the tardiness measures.

- PM tool rules perform better than the non-PM rule (NOPM) in most cases. PM rules reduce the amount of tool failures and thus maintenance delays. It should be noted that the NOPM tool rule performs better than tool rules VARLO and JDDTL on several measures.

Vanderhenst et al. (1981), and Banerjee and Burton (1990) point out that CM allow for a more efficient utilization of the tooling resource. The maintenance delay incurred by NOPM is less than the tool rules VARLO and JDDTL, which allow for PM. Their total time in maintenance (CM + PM + maintenance queue time) is greater than that incurred by NOPM. VARLO and JDDTL thus suffers from the worse conditions associated with both CM and PM. For example, frequently there is not enough PM to reduce tool failures, yet too much causes a higher level of total maintenance time.

- Fixed PM point (FPTPM) does not perform as well as variable PM rules. The exception is, when the variable PM tool rule allows for postponed PM. Once again, the superior performance of VARHI and VARPM over FPTPM can be attributed to total maintenance time (tool failure). The FPTPM tool rule forces a tool to remain available for production until it passes the PM point, after which, it can go in for maintenance. This inflexibility causes the risk and number of tool failures to increase. Both VARHI and VARPM allow for early removal of tools for PM, thus reducing tool failures.

- The form of variable PM, whether early or late, is a major factor in shop performance. The early PM rule VARHI consistently gives better performance than the postponed PM tool rule VARLO. While both rules consider shop demand, the difference in performance can be contributed to tool failure risk. The higher risk results in greater frequency of tool failures and higher total maintenance time.

- The use of maintenance queue information improves the performance of a variable PM tool rule. The MQBPM rule is a modified VARPM tool rule with the addition of maintenance queue information. Examining maintenance queue and allowing removal of tools for PM causes reduced tool failure risk. Total maintenance time is also lower for MQBPM than for VARPM. While the use of maintenance queue information improves performance on a number of measures, it causes a greater variation in performance. Thus, MQBPM performs worse than VARPM for the standard deviation performance measures.

- Allowing tools to remain in production until all past due jobs are done does not improve delivery performance (tardiness and percentage of jobs late). The tool rule JDDTL performed significantly worse than FPTPM because it forces a tool to remain in production. The high risks of tool failures negates any benefit that delayed PM could provide. Whenever presented with the choice to perform PM or process a job when past the PM point, the results show that the tool should be removed for PM.

- The last issue, the effects of variance, is not as clear-cut as this research might indicate. While tool life and maintenance variance is inconsequential, this only reflects the parameters used in the model.

6.4 Post Hoc Analysis

The following analysis consists of two parts. The first part will examine the relative performance of tool control and job priority rules since these rules dominate the influence on shop performance. The control rules will be examined under low and high tool life and maintenance service variance. The objective is to determine the robustness of the control rules and further investigate their affect.

The second part will examine the performance of combined tool control rules and job priority rules. The objective here is to determine what combination of rules provide the best overall performance.

While post hoc analysis does not provide the same level of construct validity as a priori analysis, it does allow further investigation and insights. The purpose of the post hoc analysis is to provide insight into how the tool and job heuristics perform. Tukey HSD multiple comparisons will be used to conduct the analysis. The significant differences found in the Tukey test which are not found in the ANOVA tests can be attributed to the techniques used in comparing treatments. ANOVA compares the mean of the means to each treatment mean. Whereas, Tukey compares each treatment mean to each other.

6.4.1 Relative Performance of Heuristics

The introduction and HIGH and LOW variance consist of two parts: 1) tool life, and 2) maintenance. Two specific items will be examined when analyzing the multiple comparison tables. The first concern looks at how the relative performance of each heuristic is affected by variance. Does the rule perform well under LOW or HIGH variance? The second issue, is there any cross over effect to different levels of variance? This looks at whether a heuristic performs better for HIGH variance than LOW variance.

6.4.1.1 Tool Life Variance

Each performance measure, except mean time in system, show significantly different groups of job priority rules (Table 6-23a). The rank order of the job rules show that those job rules which perform well under LOW variance do equally well under HIGH variance. The exception is, mean time in system and log percentage of tool failures (Table 6-23a). What is seen for these two performance measures is grouping of job rules under LOW and HIGH variance. Also, in no case does a job rule perform better under HIGH variance than under LOW variance (Figures 6-16 a-f).

When examining tool control rules by tool life variance, there are significant differences between certain rules (Table 6-23b). The tool rules which perform well under LOW variance also do so under HIGH tool life variance. Tool rules perform better under LOW variance than HIGH variance.

Table 6-23a Tukey Multiple Comparisons of Job Priority Rules by Tool Life Variance.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4-LOW	PSR4-LOW	PSR4-LOW	PSR4-LOW	SDTC-LOW	SDTC-LOW
DRTC-LOW	PSR4-HIGH	PSR4-HIGH	PSR4-HIGH	SDTC-HIGH	PSR4-LOW
SDTC-LOW	DRTC-LOW	DRTC-LOW	DRTC-LOW	SSTL-LOW	DRTC-LOW
PSR4-HIGH	DRTC-HIGH	DRTC-HIGH	DRTC-HIGH	SSTL-HIGH	SSTL-LOW
DRTC-HIGH	SDTC-LOW	SDTC-LOW	SDTC-LOW	DRTC-LOW	SDTC-HIGH
SDTC-HIGH	SDTC-HIGH	SDTC-HIGH	SDTC-HIGH	DRTC-HIGH	PSR4-HIGH
SSTL-LOW	SSTL-LOW	SSTL-LOW	SSTL-LOW	PSR4-LOW	DRTC-HIGH
SSTL-HIGH	SSTL-HIGH	SSTL-HIGH	SSTL-HIGH	PSR4-HIGH	SSTL-HIGH

Table 6-23b Multiple Comparisons Of Tool Control Heuristics and Tool Life Variance

Mean Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tools Failures
VARHI-LOW	VARHI-LOW	VARHI-LOW	VARHI-LOW	VARHI-LOW	MQBPM-LOW
MQBPM-LOW	VARPM-LOW	MQBPM-LOW	VARPM-LOW	MQBPM-LOW	VARHI-LOW
MQBPM-HIGH	VARHI-HIGH	MQBPM-HIGH	VARHI-HIGH	FPTPM-LOW	MQBPM-HIGH
VARHI-HIGH	MQBPM-LOW	VARPM-LOW	VARLO-LOW	MQBPM-HIGH	VARHI-HIGH
VARPM-LOW	MQBPM-HIGH	VARHI-HIGH	VARLO-HIGH	VARHI-HIGH	VARPM-LOW
VARPM-HIGH	VARPM-HIGH	VARLO-LOW	NOPM-LOW	VARPM-LOW	VARPM-HIGH
FPTPM-LOW	VARLO-LOW	VARPM-HIGH	NOPM-HIGH	VARPM-HIGH	FPTPM-LOW
FPTPM-HIGH	VARLO-HIGH	VARLO-HIGH	MQBPM-LOW	JDDTL-LOW	FPTPM-HIGH
VARLO-LOW	NOPM-LOW	NOPM-LOW	VARPM-HIGH	FPTPM-HIGH	JDDTL-LOW
VARLO-HIGH	NOPM-HIGH	NOPM-HIGH	MQBPM-HIGH	JDDTL-HIGH	JDDTL-HIGH
JDDTL-LOW	FPTPM-LOW	FPTPM-LOW	FPTPM-LOW	VARLO-LOW	VARLO-LOW
JDDTL-HIGH	FPTPM-HIGH	FPTPM-HIGH	FPTPM-HIGH	VARLO-HIGH	VARLO-HIGH
NOPM-LOW	JDDTL-LOW	JDDTL-LOW	JDDTL-LOW	NOPM-LOW	NOPM-LOW
NOPM-HIGH	JDDTL-HIGH	JDDTL-HIGH	JDDTL-HIGH	NOPM-HIGH	NOPM-HIGH

Figure 6-16a Comparison of Job Priority Rules by Tool Life Variance
for Mean Time in System

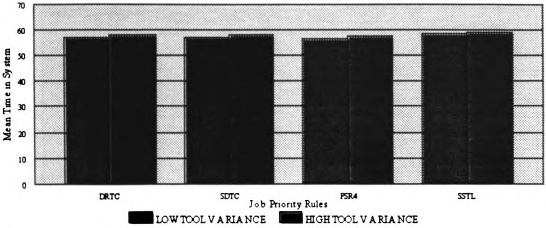


Figure 6-16b Comparison of Job Priority Rules by Tool Life Variance
for Standard Deviation Time In System

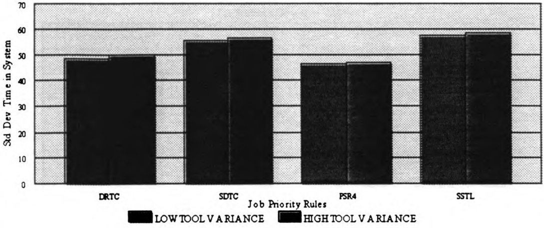


Figure 6-16c Comparison of Job Priority Rules by Tool Life Variance

for Mean Tardiness

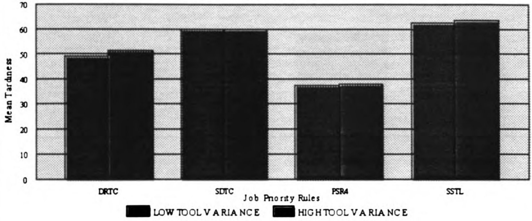


Figure 6-16d Comparison of Job Priority Rules by Tool Life Variance

for Standard Deviation Tardiness

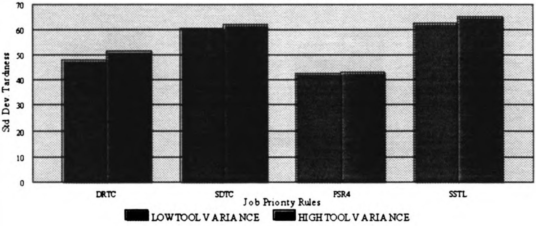


Figure 6-16e Comparison of Job Priority Rules by Tool Life Variance
for Percentage of Jobs Late

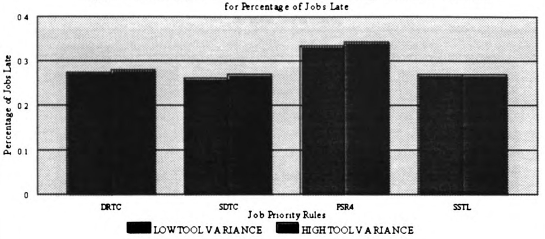


Figure 6-16f Comparison of Job Priority Rules by Tool Life Variance
for Percentage of Tool Failures

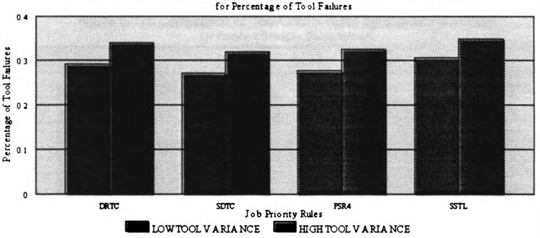


Figure 6-17a Comparison of Tool Control Rules by Tool Life Variance
for Mean Time in System

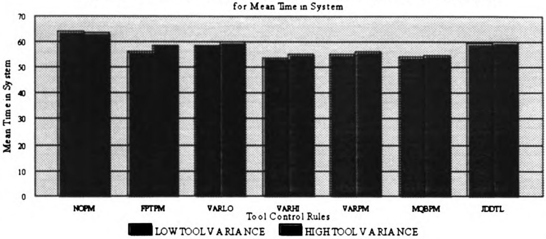


Figure 6-17b Comparison of Tool Control Rules by Tool Life Variance
for Standard Deviation Time in System

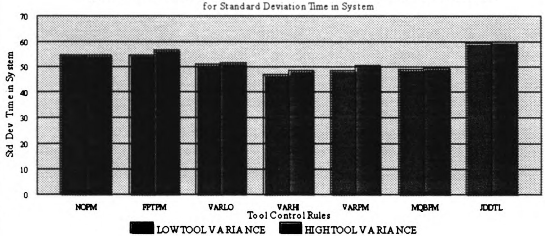


Figure 6-17c Comparison of Tool Control Rules by Tool Life Variance

for Mean Tardiness

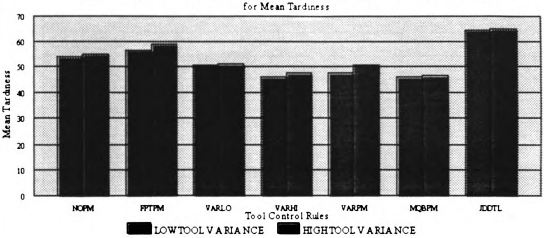


Figure 6-17d Comparison of Tool Control Rules by Tool Life Variance

for Standard Deviation Tardiness

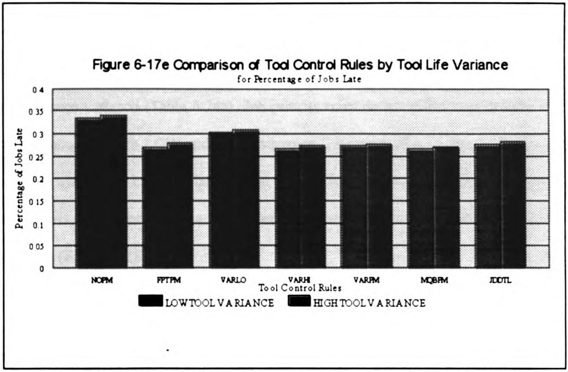


Figure 6-17e Comparison of Tool Control Rules by Tool Life Variance
for Percentage of Jobs Late
Percentage of Jobs Late
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules
LOW TOOL VARIANCE
HIGH TOOL VARIANCE

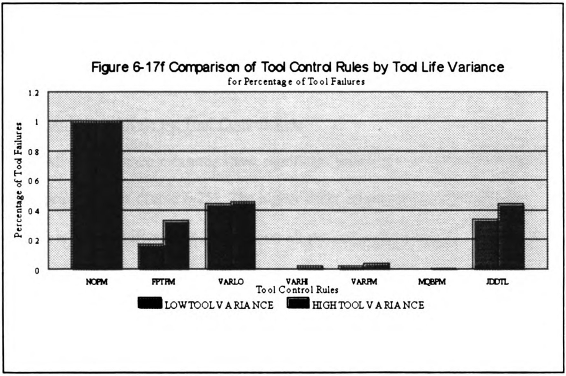


Figure 6-17f Comparison of Tool Control Rules by Tool Life Variance
for Percentage of Tool Failures
Percentage of Tool Failures
1.2
1
0.8
0.6
0.4
0.2
0
NOPM
FPTPM
VARLO
VARHI
VARPM
MQBPM
JDDTL
Tool Control Rules
LOW TOOL VARIANCE
HIGH TOOL VARIANCE

6.4.1.2 Maintenance Service Time Variance

All performance measures except, mean time in system and log percentage of tool failures show significant differences between treatments for job rule by maintenance variance (Table 6-24a). Job priority rules do not differ significantly in performance between LOW and HIGH variance (Figures 6-18 a-f). Job rules which perform well under LOW variance do so under HIGH maintenance variance. There is no cross over effect where a rule under HIGH variance performs better than LOW variance (Figure 6-18 a-f).

All performance measures show groupings of significant differences between tool rule by maintenance variance (Table 6-24b). Tool control rules do not significantly differ between HIGH and LOW maintenance variance (Table 6-24b). Tool rules which perform well under LOW variance, also perform almost equally as well under HIGH variance. No tool rule exhibited cross over effect.

6.4.2 Job Priority Rule by Tool Control Rule

All performance measures show significant groupings of various tool control by job priority rules (Table 6-25). The higher order interaction of MTOOL by NRULE is also significant for ANOVA on all performance measures in the analysis of effects. The groupings of significantly different job-tool rules make comparisons difficult. For this reason, the rank order of combined rules will be used to draw conclusions.

For mean time in system measure, the tool control rule has more influence on

Table 6-24a Tukey Multiple Comparisons of Job Priority Rules by Maintenance Service Variance.

Mean Time In System	Standard Deviation Time In System	Mean Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tool Failures
PSR4-LOW	PSR4-LOW	PSR4-LOW	PSR4-LOW	SDTC-LOW	SDTC-LOW
PSR4-HIGH	PSR4-HIGH	PSR4-HIGH	PSR4-HIGH	SDTC-HIGH	PSR4-LOW
DRTC-LOW	DRTC-LOW	DRTC-LOW	DRTC-LOW	SSTL-LOW	SDTC-HIGH
DRTC-HIGH	DRTC-HIGH	DRTC-HIGH	DRTC-HIGH	SSTL-HIGH	DRTC-LOW
SDTC-LOW	SDTC-LOW	SDTC-LOW	SDTC-LOW	DRTC-LOW	PSR4-HIGH
SDTC-HIGH	SDTC-HIGH	SDTC-HIGH	SDTC-HIGH	DRTC-HIGH	SSTL-LOW
SSTL-LOW	SSTL-LOW	SSTL-LOW	SSTL-LOW	PSR4-LOW	DRTC-HIGH
SSTL-HIGH	SSTL-HIGH	SSTL-HIGH	SSTL-HIGH	PSR4-HIGH	SSTL-HIGH

Table 6-24b Multiple Comparisons Of Tool Control Heuristics by Maintenance Service Variance

Mean Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tools Failures
VARHI-LOW	VARHI-LOW	MQBPM-LOW	VARHI-LOW	MQBPM-LOW	MQBPM-LOW
MQBPM-LOW	VARHI-HIGH	MQBPM-HIGH	VARPM-LOW	MQBPM-HIGH	MQBPM-HIGH
MQBPM-HIGH	VARPM-LOW	VARHI-LOW	VARHI-HIGH	VARHI-LOW	VARHI-LOW
VARHI-HIGH	MQBPM-LOW	VARHI-HIGH	VARLO-LOW	VARHI-HIGH	VARHI-HIGH
VARPM-LOW	MQBPM-HIGH	VARPM-LOW	VARLO-HIGH	FPTPM-LOW	VARPM-LOW
VARPM-HIGH	VARPM-HIGH	VARPM-HIGH	NOPM-HIGH	VARPM-LOW	VARPM-HIGH
FPTPM-LOW	VARLO-LOW	VARLO-LOW	NOPM-LOW	FPTPM-HIGH	FPTPM-LOW
FPTPM-HIGH	VARLO-HIGH	VARLO-HIGH	VARPM-HIGH	VARPM-HIGH	FPTPM-HIGH
VARLO-LOW	NOPM-HIGH	NOPM-LOW	MQBPM-LOW	JDDTL-LOW	JDDTL-LOW
VARLO-HIGH	NOPM-LOW	NOPM-HIGH	MQBPM-HIGH	JDDTL-HIGH	JDDTL-HIGH
JDDTL-LOW	FPTPM-LOW	FPTPM-LOW	FPTPM-LOW	VARLO-LOW	VARLO-LOW
JDDTL-HIGH	FPTPM-HIGH	FPTPM-HIGH	FPTPM-HIGH	VARLO-HIGH	VARLO-HIGH
NOPM-LOW	JDDTL-LOW	JDDTL-LOW	JDDTL-LOW	NOPM-LOW	NOPM-LOW
NOPM-HIGH	JDDTL-HIGH	JDDTL-HIGH	JDDTL-HIGH	NOPM-HIGH	NOPM-HIGH

Figure 6-18a Comparison of Job Priority Rules by Maintenance Service Variance
for Time in System

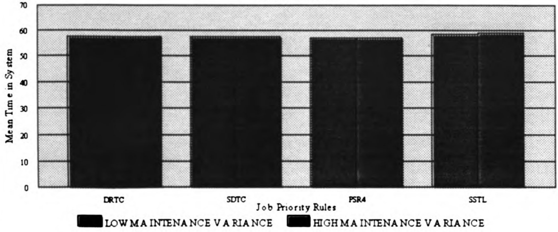
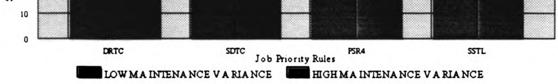


Figure 6-18b Comparison of Job Priority Rules by Maintenance Service Variance
for Standard Deviation Time in System



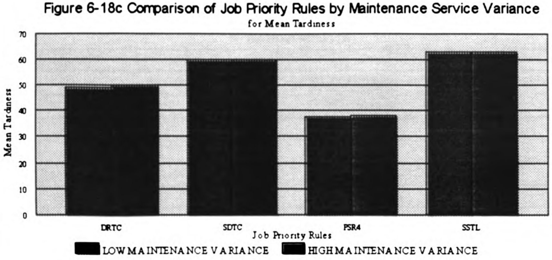


Figure 6-18c Comparison of Job Priority Rules by Maintenance Service Variance
for Mean Tardiness
Mean Tardiness
0
10
20
30
40
50
60
70
DRTC
SDTC
PSR4
SSTL
Job Priority Rules
LOW MAINTENANCE VARIANCE
HIGH MAINTENANCE VARIANCE

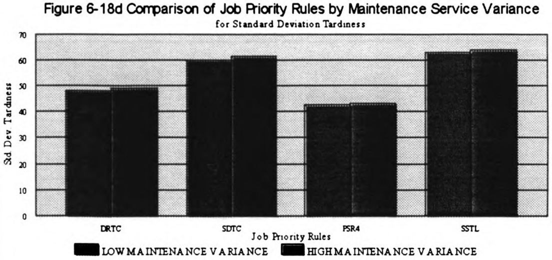


Figure 6-18d Comparison of Job Priority Rules by Maintenance Service Variance
for Standard Deviation Tardiness
Std. Dev. Tardiness
0
10
20
30
40
50
60
70
DRTC
SDTC
PSR4
SSTL
Job Priority Rules
LOW MAINTENANCE VARIANCE
HIGH MAINTENANCE VARIANCE

Figure 6-18e Comparison of Job Priority Rules by Maintenance Service Variance for Percentage of Jobs Late

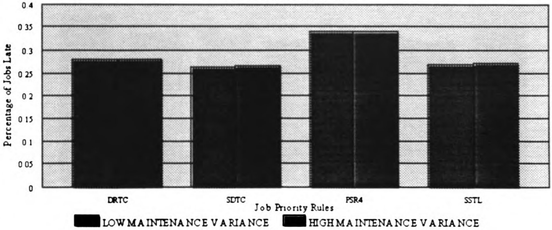


Figure 6-18f Comparison of Job Priority Rules by Maintenance Service Variance for Percentage of Tool Failures

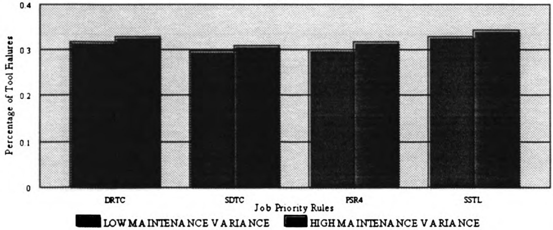


Figure 6-19a Comparison of Tool Control Rules by Maintenance Service Variance
for Mean Time in System

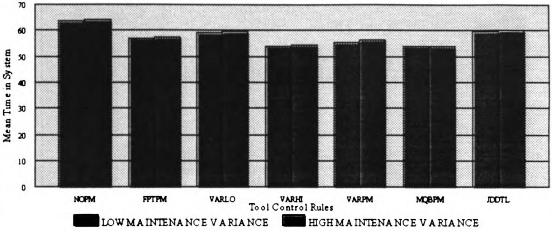


Figure 6-19b Comparison of Tool Control Rules by Maintenance Service Variance
for Standard Deviation Time in System

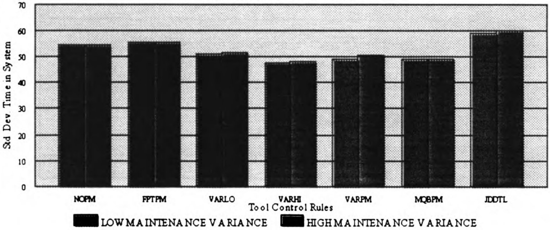


Figure 6-19c Comparison of Tool Control Rules by Maintenance Service Variance

for Mean Tardiness

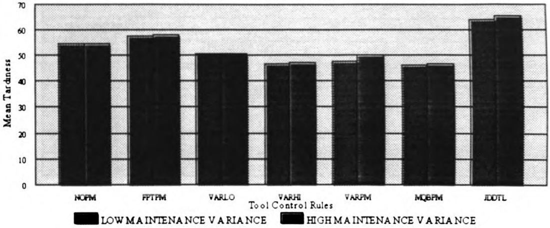


Figure 6-19d Comparison of Tool Control Rules by Maintenance service Variance

for Standard Deviation Tardiness

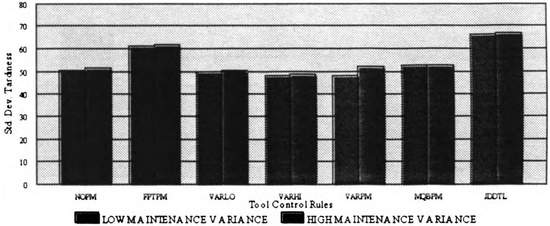


Figure 6-19e Comparison of Tool Control Rules by Maintenance Service Variance
for Percentage of Jobs Late

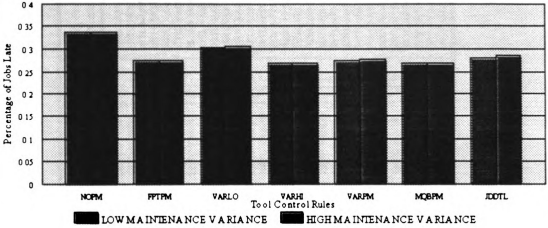


Figure 6-19f Comparison of Tool Control Rules by Maintenance Service Variance
for Percentage of Tool Failures

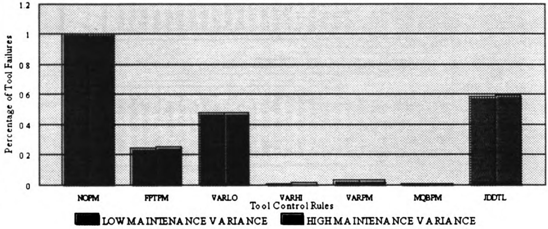


Table 6-25 Tukey Multiple Comparisons Of Job Priority Rules by Tool Control Rules

Mean Time In System	Standard Deviation Time In System	Tardiness	Standard Deviation Tardiness	Percentage of Jobs Late	Log Percentage of Tools Failures
PSR4-MQBPM	DRTC-VARHI	PSR4-MQBPM	DRTC-VARHI	DRTC-FPTPM	PSR4-MQBPM
SDTC-MQBPM	PSR4-MQBPM	PSR4-VARHI	DRTC-VARLO	SSTL-MQBPM	SDTC-MQBPM
SDTC-VARHI	PSR4-VARHI	PSR4-FPTPM	PSR4-NOPM	SSTL-VARHI	SSTL-MQBPM
PSR4-VARHI	DRTC-VARLO	PSR4-VARPM	DRTC-NOPM	SDTC-MQBPM	DRTC-MQBPM
SDTC-VARPM	DRTC-NOPM	PSR4-JDDTL	PSR4-VARHI	DRTC-JDDTL	SDTC-VARHI
DRTC-VARHI	DRTC-VARPM	DRTC-VARHI	PSR4-MQBPM	SDTC-VARHI	SDTC-VARPM
SSTL-MQBPM	PSR4-FPTPM	PSR4-VARLO	PSR4-FPTPM	SDTC-VARPM	PSR4-VARHI
DRTC-MQBPM	PSR4-VARPM	PSR4-NOPM	PSR4-VARPM	SDTC-FPTPM	SSTL-VARHI
SSTL-VARHI	PSR4-NOPM	DRTC-MQBPM	DRTC-VARPM	SDTC-JDDTL	DRTC-VARHI
PSR4-VARPM	DRTC-MQBPM	DRTC-VARLO	PSR4-VARLO	SSTL-FPTPM	PSR4-VARPM
DRTC-VARPM	PSR4-JDDTL	DRTC-NOPM	PSR4-JDDTL	SSTL-VARPM	DRTC-VARPM
PSR4-FPTPM	PSR4-VARLO	DRTC-VARPM	SDTC-VARHI	SSTL-JDDTL	SSTL-VARPM
SSTL-VARPM	SDTC-VARHI	SDTC-VARHI	DRTC-MQBPM	DRTC-VARPM	SSTL-FPTPM
DRTC-FPTPM	SDTC-MQBPM	SDTC-MQBPM	SDTC-VARPM	DRTC-VARHI	PSR4-FPTPM
SSTL-FPTPM	SDTC-VARPM	SDTC-VARPM	SDTC-MQBPM	DRTC-MQBPM	DRTC-FPTPM
SDTC-FPTPM	SSTL-MQBPM	SSTL-MQBPM	SDTC-VARLO	SDTC-VARLO	SDTC-FPTPM
PSR4-JDDTL	SSTL-VARPM	SSTL-VARPM	SSTL-VARPM	SSTL-VARLO	PSR4-JDDTL
DRTC-VARLO	SSTL-VARHI	SSTL-VARHI	SSTL-VARLO	DRTC-VARLO	SDTC-JDDTL
PSR4-VARLO	SDTC-VARLO	SSTL-VARLO	SDTC-NOPM	SSTL-NOPM	SSTL-JDDTL
SDTC-VARLO	SSTL-VARLO	SDTC-VARLO	SSTL-FPTPM	PSR4-MQBPM	SDTC-VARLO
SDTC-JDDTL	DRTC-FPTPM	SDTC-NOPM	SSTL-MQBPM	PSR4-VARHI	DRTC-JDDTL
DRTC-JDDTL	SSTL-FPTPM	SSTL-FPTPM	DRTC-FPTPM	SDTC-NOPM	PSR4-VARLO
SSTL-VARLO	SDTC-NOPM	DRTC-FPTPM	SSTL-VARHI	PSR4-VARHI	DRTC-VARLO
SSTL-JDDTL	SDTC-FPTPM	SDTC-FPTPM	SSTL-NOPM	DRTC-NOPM	SSTL-VARLO
DRTC-NOPM	DRTC-JDDTL	SSTL-NOPM	SSTL-JDDTL	PSR4-FPTPM	SSTL-NOPM
PSR4-NOPM	SSTL-JDDTL	SDTC-JDDTL	DRTC-JDDTL	PSR4-JDDTL	PSR4-NOPM
SDTC-NOPM	SDTC-JDDTL	DRTC-JDDTL	SDTC-FPTPM	PSR4-VARLO	SDTC-NOPM
SSTL-NOPM	SSTL-NOPM	SSTL-JDDTL	SDTC-JDDTL	PSR4-NOPM	DRTC-NOPM

performance. The tool rules, MQBPM, VARHI, and VARPM are the best performers regardless of job priority rule. The job priority rules influence cause variation in the relative performance. For example, when job rules PSR4 and SDTC are combined with MQBPM, VARHI, and VARPM, performance for mean time in system tends to be the best. The worst tool control rule performers are NOPM, JDDTL, and VARLO. Once again, the job priority rule causes only small increases or decreases in the relative position.

For standard deviation of time in system, the consistency of performance of the rules is less certain. The job priority rules tend to play a larger role in relative performance for this measure. Job priority rules PSR4 and DRTC improve performance the most. When these two job rules are combined with VARHI and MQBPM tool rules, the best performance results. The job rules SSTL and SDTC tend to cause performance to worsen. Only the JDDTL tool control rule showed consistently poor performance.

For mean tardiness, job priority rules are more influential than tool control rules in determining performance. The first group (top) of significantly different combined rules is dominated by the PSR4 job rule, followed by DRTC. This outcome is what would be expected for job rules which prioritize by due date. It should also be noted that the first significant group contained all seven tool control rules because they were combined with job rule PSR4 (Table 6-25). The combination of SSTL and SDTC job rules with JDDTL and FPTPM tool rules results in the worst performance.

For standard deviation of tardiness, the job priority rules are also more influential than tool control rules. The job rules which promote better performance are PSR4 and DRTC, with SDTC and SSTL resulting in poorer performance (Table 6-25). As for the tool control rules, there is no clear dominate rule.

For percentage of jobs late, job priority rules SDTC provides consistently high performance, while PSR4 gives the worst performance. No clear combination of job priority and tool control rules perform best for this measure.

For log percentage of tool failures, the tool control rules influence performance more than job priority rules. The first two significantly different groupings are dominated by the tool control rules, MQBPM and VARHI. The worse performing tool rules are NOPM, VARLO, and JDDTL. No clear dominate job priority rule can be found (Table 6-25).

6.4.3 Summary of Post Hoc Analysis

Results from the post hoc analysis confirm findings found in the analysis of effects and a prior analysis. The following is a summary of the post hoc analysis.

- The relative performance of both job priority and tool control rules are not affected by tool life and maintenance service variance (also evidenced in the ANOVA results). Control rules perform better under LOW variances than HIGH with little difference between each level. This is to be expected since shop performance generally deteriorates under high variance. The better performing tool rules (MQBPM and VARHI) exhibit robustness for both forms of variance. MQBPM and VARHI tool rules also exhibit robustness across performance measures. The job priority rules (PSR4 and DRTC) also exhibit robustness in the presences of variance. The job priority rules do not exhibit robustness with respect to performance measures. The PSR4 rule gives the best performance on most measures, except percentage of jobs late where it performs worse.

- No job priority or tool control rule exhibited cross-over effect. While the result was expected, this may not always hold true under different model parameters.

- No single combination of tool and job rules perform best for all performance measures. The most consistently high performance is obtained when the PSR4 job rule is combined with either MQBPM or VARHI tool rules. It should be noted that both PSR4 job rule and MQBPM tool rules are information intensive. Both heuristics consider more conditions in their decision process then most other rules. Clearly, this shows additional information is beneficial.

6.5 Discussion of Results

The analysis of effects, a priori hypothesis, and post hoc analysis found that two tool control rules, MQBPM and VARHI, consistently outperform all other tool rules. As for job priority rules, PSR4 provides the best performance except for percentage of jobs late. There are however, a number of results which did not conform to expectations. The following is a discussion of why the outcomes differed.

The expected outcome that SSTL job rule would outperform SDTC rule was based on past research (Lyman, 1993). Job rules which considered tool utilization improved performance under deterministic tool life. This model used stochastic (unknown) tool life. By selecting the tool which can be utilized the longest on a machine, a slight increase in tool failures was observed. This lowered the performance of SSTL. The other reason SSTL performed poorly is that it did not give consideration to job due date when tool change took place. This causes further worsening of SSTL's performance.

The job rule SDTC considers due date for all jobs in queue when tool changes take place. For this reason, SDTC performed slightly better than SSTL. Both SDTC and SSTL suffer because they are myopic. They attempt to fully utilize an existing tool setup without considering all jobs in queue due dates.

Neither SDTC nor SSTL perform better than the PSR4 job rule. PSR4 rule, like SSTL and SDTC, allow sequence dependency to utilize existing tool setup (Melnyk et al., 1989). The advantage of PSR4 is the rule re-examines the machine queue in its entirety after each job is completed. The re-examination allows the PSR4 rule more information in its decision process, thus giving it top performance among all the job rules.

The exception for PSR4 job rule is the percentage of jobs late performance measure. The reason for this poor performance can be explained by the priority setting. Priorities are set by job slack and setup requirements. While PSR4 rule responds quickly to jobs which are past due (negative slack), this increases the number of jobs late while simultaneously keeping mean and standard deviation of tardiness low. To improve PSR4 job rule on percentage of jobs late requires only a minor modification to the job slack value.

The use of due date information is essential in shop performance. Both PSR4 and DRTC job priority rules use due date status of all jobs when deciding which job to process next. Both rules perform consistently well on the performance measures as well as being robust to system variance. The evidence shows that the key piece of information for job priority rules is due date status with setup requirements playing a minor role in performance.

While results in this study generally confirms results from past research (Melnyk et al., 1989; Lyman, 1993), it also contradicts certain research. The conclusions that sequence dependency is a key determinate in shop performance is not supported in this model. Articles by Mahmoodi et al. (1990), Mahmoodi and Dooley (1991), and Kannan and Lyman (1992) support the position that sequence dependant rules (family rules) improve performance. In the model used for this research, sequence dependant job rules result in worse performance. This conclusion is based on a lower setup time to processing time ratio (20% vs. 33%) and in the presences of finite life tooling resource.

There were a number of surprising results that occurred with the tool control heuristics. While it was expected that PM tool rules would outperform the CM tool rule, there are a number of exceptions. The results confirm past research of Kay (1978) and Banerjee and Burton (1990) by pointing out that PM is preferred in most cases. Banerjee and Burton showed that some PM rules can decrease performance because of maintenance frequency.

The poor performing PM tool rules, JDDTL and FPTPM, suffer from higher total maintenance time. These rules cause high frequency of tool failures and thus suffer the plight that NOPM tool rule does. JDDTL and FPTPM tool rules also do not benefit from PM to the extent that tool rules MQBPM and VARHI do. The result is higher maintenance time due to tool failures compared to VARHI and more frequent maintenance trips than NOPM. The higher frequency allows NOPM to outperform JDDTL and FPTPM on several performance measures. Table 6-26 provide an illustration of how PM tool rule can perform better or worse than the CM tool rule.

Table 6-26 Example of Total Maintenance Time

TOOL RULE	NUMBER OF CM	MAINTENANCE TIME FOR CM (6 Hours)	NUMBER OF PM	MAINTENANCE TIME FOR PM (3 Hours)	TOTAL TIME
NOPM	30	180	0	0	180
JDDTL	17	102	30	90	192
VARHI	2	12	45	135	147

Other results which did not conform to expectations was that of hypothesis 4. Results showed that allowing early PM (VARHI and VARPM) outperform the fixed point PM rule (FPTPM). The unexpected result is that variable PM rule VARLO does not outperform FPTPM. This points out an interesting conclusion. Early PM reduces the risk of tool failure, which increases tool availability via less maintenance delay. Higher tool availability increases shop performance. Past work by Banerjee and Burton (1990) and Pete-Cornell et al. (1987) found that shop performance decreases with high PM frequency. Conversely, the more frequent PM under tool rules VARHI and VARPM contradict these past findings. The tool rules VARLO and FPTPM cause a higher frequency of tool failures, thus lowering performance.

As stated previously, VARHI tool rule outperforms VARLO for the reason cited above. In Hypothesis 5, it is stated that the reverse would hold true, VARLO would outperform VARHI. Clearly, the added risk to process an additional job is not beneficial, but detrimental to performance. This same conclusion can also be applied to Hypothesis 7. The added tool failure risk that rule JDDTL allows, actually causes all performance measures to worsen when compared to FPTPM.

The results of Hypothesis 6 are as expected, the use of maintenance queue information does improve shop performance. The logic behind MQBPM tool rule is similar to that of VARHI, which encourages early PM when conditions permit. While these two rules may not operate identically, the results show they perform equally well.

The key component to shop performance for this model as well as in past models is tool (resource) availability (Melnyk et al., 1989). This conclusion can be seen in the performance of the various tool control rules. The tool rules, MQBPM and VARHI, cause the least tool failures and thus the shortest total maintenance service delay. The less time spent in the maintenance process the greater tool availability. If PM is too frequent, the result will be decrease shop performance (Banerjee and Burton, 1990).

The tool heuristics developed for this model take the perspective actually used on shop floors. If there is a past due job which needs a tool, keep the tool in production as long as the tool's limits have not been surpassed. When the choice is between processing jobs early (prior to due date) versus sending a tool in for maintenance, choose maintenance. This is especially true for the MQBPM tool rule which uses maintenance queue information. If there is no backlog of tools (queue is empty) waiting for maintenance, then its advantageous to seize the opportunity. The other advantage to the use of maintenance queue information is that tool repairs can be spread out, allowing balanced maintenance workload.

This last point brings up the issue of planned and unplanned maintenance. While not considered explicitly by the PM tool rules, they do implicitly plan maintenance. Past articles have pointed to the need and benefits of planned maintenance (Bojanowski, 1984; Christer and Whitelaw, 1988). This research has demonstrated that PM is beneficial compared to CM. Further, the ability to balance maintenance workload through the MQBPM tool rule is similar to planned maintenance. If planned maintenance is to be truly effective, then it must balance maintenance workload while simultaneously considering shop floor demand. Linking the maintenance process to the shop floor schedule or MRP schedule would accomplish this task.

The results from this experiment has contributed to further understanding in a number of ways. The use of information, both type and frequency, can improve shop performance. While past research supports this proposition (e.g. Fredendall, 1991), this research highlights the benefits of information in a stochastic environment. This includes the use of job due date status and setup requirements. When job due date is checked intermittently, shop performance deteriorates significantly.

The use of information in the tool decision is also a major factor in shop performance. Maintenance queue backlog information allows the tool rule MQBPM to significantly out perform rule VARPM. Information on shop floor demand also leads to the success of the variable PM rules. By evaluating job demand, the tool rules can evaluate whether there is a need to keep the tool in production or allow for early PM.

This research has also contributed by developing a number of unique tool control rules. Past research has focused almost exclusively on fixed point PM rules (Banerjee and Burton, 1990; Christer and Whitelaw, 1984). The results from this research indicate that variability in the PM decision can improve performance over the fixed PM point rules. The variability allows for consideration of such factors as: shop demand, tool condition and maintenance load. This provides the decision maker the opportunity to evaluate the environment and make an informed decision.

The last contribution of this research is the recognition that control of a finite life resource requires a different approach. Whereas past DRC research has viewed the resources of labor and machine as having infinite life, this model replaces labor with a finite life resource (tooling). This changes the characteristics of the DRC model. To control a finite life resource requires the development of new heuristics.

Control heuristics which work for labor are inappropriate for tooling. Research by Nelson (1966), Goodman (1972) and Fryer (1974, 1978) point out that the *where* to send and *when* to send a resource. With finite life resource, an additional series of questions must be asked: 1) is the resource available, 2) how much of the resource is remaining, and 3) is that sufficient life? While this adds complexity to the control heuristics, these rules are more representative of the real decision made on the shop floor.

6.6 Summary of Analysis

Results show that the factors, tool control rules (MTOOL) and job priority rules (NRULE), are the determinates of shop performance. Of these rules, several stand out as effective and robust. The early variable PM rules, MQBPM and VARHI, when combined with PSR4 job rule provide consistently high performance. While variable PM gives better performance over fixed point PM tool rules FPTPM and JDDTL, this flexibility is not totally beneficial. The expectation that variable PM tool rules which postpones PM would improve performance, especially tardiness, was not realized. In fact, the opposite was true.

The expectation that sequence dependant job priority rules SSTL and SDTC would improve performance was not realized. The poor performance is attributed to the fact that: 1) the setup to processing ratio is 20 percent, and 2) to their myopic focus on machine/tool setup. The job priority rule DRTC, while not performing as well as PSR4 rule, does provide fairly robust performance. DRTC focuses on job due date as its priority and thus performs better on those measures which focus on delivery performance.

6.7 Future Research Directions

The experimental condition and results suggest several future research avenues. The following is a brief description of possible extensions.

- The relationship of the PM point to mean tool life needs further examination. This can be accomplished by adjusting the PM point relative to mean tool life. By changing the parameters of the model, examination of the tool control rules will illustrate how they differ under various environments. Should the PM point be moved further from mean tool life, such tool rules as VARLO or FPTPM may improve in their performance. Examining different PM points will allow for a more appropriate placement of the PM point or aid in the development of simpler yet effective PM tool rules. While Banerjee and Burton (1990) varied the PM point, they only examine the effect of such a change on a fixed PM point rule.

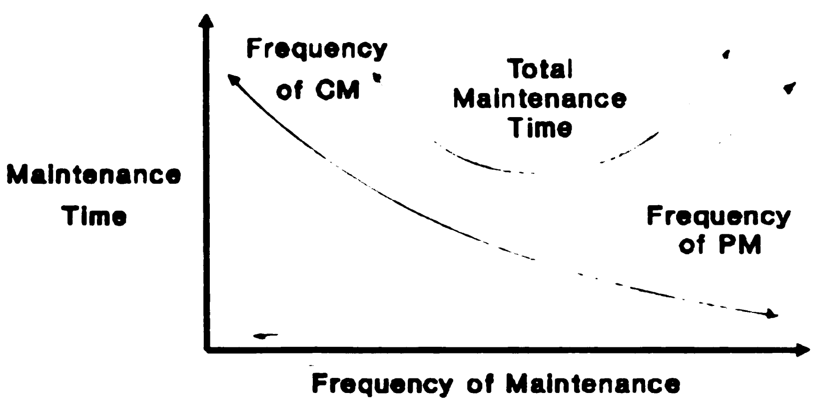
- Another tool control rule issue which needs to be explored further involves the degree of variability in the variable PM tool rules. The results of this study has found that the use of variable PM provides the best performance. Since this research is the first known work which tests a variable range for the PM decision, additional tests are needed. Adjusting the current 10% range for variable PM to several values both higher and lower will be necessary. This will provide a wider range of information on what is an appropriate range for a variable PM tool control rule.

Such information would benefit managers who are establishing parameters for a maintenance program.

- A third issue which must be explored is tool life distribution. The use of a normal distribution was selected because of discussions during plant visits and several articles (Lie et al., 1977; Fenton and Joseph, 1979). Past research has shown that varied tool life distributions like log-normal, Weibull, and gamma can alter results (Ramalingam et al., 1978; Bao, 1980). Examining the tool heuristics under different distributions will test the robustness of the control rules. Once again, the benefits to this analysis would be to provide a manager information from which to make a decision.

- The frequency of maintenance issue needs to be examined in greater detail. The results of this research contradicts the outcome found by Banerjee and Burton (1990). Figure 6-19 illustrates how frequency of maintenance and total maintenance

Figure 6-20 Total Maintenance Time



time are related. While this relationship seem straight forward, the variable PM tool rules seem to alter the shape of the total maintenance curve. Additional research needs to focus on how the various tool rules influence the relationship.

- Results from this research has shown PSR4 rule is effective for all measures, but percentage of jobs late. Modification of PSR4, plus the addition of job priority rules which consider tool availability, should be studied. While the job priority rules studied in this model considered the PM point, future job priority rules should examine remaining tool life and maintenance status. The addition of these forms of information are likely to improve performance.

- Other parameters that should be altered to develop a comprehensive understanding of tool control is tool flexibility. The use of flexibility in the PM rule has been found to improve shop performance. Would the ability to move tools between machines improve performance? Past DRC research has found labor flexibility to be beneficial (e.g. Fryer, 1974; Goodman, 1972). The likely results will show that the addition of flexibility to a resource improves performance (Swamidass, 1988). Past DRC models (e.g. Melnyk and Lyman, 1991) have developed control heuristics which are useful for labor control but are not likely to be useful with finite tool life. New control heuristics will need to be developed which consider tool life and maintenance delay.

- Another parameter issue which needs further study involves multiple copies of each tool. While this has been studied in past research (e.g. Bao, 1980; David and Purcheck, 1981). Multiple tool copies have never been studied in a DRC environment or when maintenance (PM or CM) needs to be performed. Once again, heuristics will need to be developed which incorporates the additional information. Such information as location, remaining life, and specific application will need to be considered for the effective management of the shop floor.

- The last research issue which needs further investigation is that of shop floor performance measures. The traditional DRC model has focused on measures specific to job performance (Treleven, 1988). Such measures as time in system and tardiness, while important, are not the only consideration. Fredendall (1992) used labor cost data to evaluate shop performance. The cost of tool changes and maintenance needs to be considered to evaluate the appropriateness of both tool and job heuristics. Other non-job oriented performance measures that will aide in comprehending tool rule influence includes: total maintenance time, maintenance utilization rate, and utilization rate. The different measures provide a means to further evaluate shop performance.

6.8 Conclusion

The main findings of this study consist of the following:

- Preventive maintenance improves performance over corrective maintenance in most cases.

- Preventive maintenance policies which promote early or frequent maintenance improve performance over fixed point or postponed PM policies.

- The use of certain forms of information, both in job priority and tool control rules, can improve shop performance.

- Tool life and maintenance service variance is not an influence on shop performance due to the small loss of tool availability from maintenance delay.

- Job priority rules which consider due date and setup requirements prior to job processing enhances performance the most.

The above results are the conclusions drawn from the analysis. To complete the purpose of this research there are a number of questions which must be answered that were developed in Chapter 1.

The first question: how do we schedule jobs, can be answered by examining the results of job priority rules. The PSR4 job priority rule provides the best example of how to schedule jobs in the most effective manner. The PSR4 rule considers due date, setup requirements, and tool availability when selecting a job. Scheduling of jobs requires that tool be available and then prioritizes based on either due date or setup requirements or both. The use of all three sources of information provides the best method of scheduling jobs.

The second question examines how do we effectively schedule tools for production and maintenance? The scheduling of tools for production is determined by the job priority rules. The scheduling of maintenance is determined by the tool control rules. Those rules which promote early PM or frequent maintenance provide the best performance. Allowing tools to remain in production until they fail cause shop performance to deteriorate.

Thus, tool rules provide the best means of scheduling tools for maintenance. The tool rule JDDTL, which attempts to schedule tools to be available for production at the expense of maintenance, also cause shop performance to deteriorate. Additional research needs to be conducted to explore tool scheduling that considers both production demand and planned maintenance. No rule was able to consider more than one tool at a time. By considering multiple tools simultaneously, scheduling of production and maintenance is likely to improve performance.

The third question is, how does tool life and maintenance variation affect scheduling decisions? Based on the post hoc analysis, the control heuristics exhibited robust behavior and is not influenced by either form of variance.

By answering these three specific questions, the general research question: how do we effectively manage a DRC shop given stochastic tool life and maintenance service, can be resolved. To answer this question, the most effective means to managing a DRC shop is to divide the decision process into two segments. The first segment is job selection. The use of PSR4 job priority rule provides the highest level of performance. The second segment consists of tool allocation via tool control rules. The most effective means of improving performance is through the use of variable PM rules which promote early maintenance. The best rules are VARHI and MQBPM. The combined rules PSR4-VARHI and PSR4-MQBPM provide the best and most robust set of rules. What this points to is additional information and frequent/early maintenance enhances performance.

The final part of this conclusion will focus on the application of the results obtained from this model. The model is based on information obtained from two flow shops. Thus, the results from this research are generally applicable to these two manufacturing environments. Results are not specifically applicable because the model is a combination of both environments. While both shops were similar, they differed in several ways. This includes their approach to preventive maintenance and tool control. The results do indicate that the shop which promotes frequent PM is following the best approach. To confirm these results, additional tests will be necessary using assumptions which more closely simulate the specific environment.

The generalizability of the results obtained from this study is limited to those shop environments which emulate the assumptions used. The DRC model is not indicative of shop environments because there are only two constrained resources. The shops which were visited have additional constraints like labor and materials. These shops also operated under different assumptions, like machine failure and tool flexibility, than those used in this model. To conclude that the results from this study are applicable under all constraints and assumptions, would not be valid. It should also be noted, that the results from this flow shop model may not be applicable to job shops. What this illustrates is the need for additional research. By adding additional constraints and modifying the assumptions, it may then be possible to apply the results to a specific shop or develop a framework from which results can be generalized to all shop environments.

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