SINGLE STAGE BI-CRITERIA
MASTER PRODUCTION SCHEDULING WITH
SEQUENCE DEPENDENT CHANGEOVERS
IN PROCESS INDUSTRIES

DISSERTATION

Presented in Partial Fulfillment of the Requirements for

the Degree Doctor of Philosophy in the Graduate School of

The Ohio State University

By

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*****

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ABSTRACT

This dissertation examines heuristic scheduling methods that improve master production scheduling (MPS) performance for single stage bi-criteria make-to-stock products with sequence dependent changeovers in process industries. The two criteria are defined in terms of process changeover time and order lateness. These three scheduling heuristics represent three different approaches to heuristic design. They are: (1) global interchange (3OPT); (2) Construction heuristic; and (3) random search (Simulated Annealing).

Simulation experiments along with a 4-Way ANOVA design are reported that test the performance of the 3OPT, Construction, and Simulated Annealing heuristics in reducing process changeover time and order lateness. These heuristics are tested against three performance measurements: (1) percent improvement in process changeover time against the MPS; (2) percent improvement in order lateness against the MPS; (3) percent over optimal solution. Operating conditions frequently encountered in process industries provide the operating environment. Two decision variables: (1) scheduling heuristics; and (2) tradeoff parameter and two operating variables: (1) problem size; and (2) coefficient of variation of changeover matrix make up the 4-way ANOVA design.
The results indicate that the operating conditions have a significant effect on performance of the three scheduling heuristics, and there is a significant interaction among the scheduling heuristics and the operating conditions. The results indicate that the construction heuristic provides major improvement in process changeover time against the MPS for large problems in comparison with 3-OPT and SA. Simulated Annealing and 3-OPT provide major improvement in both process changeover time and order lateness under a high coefficient of variation setting. 3-OPT and SA perform well against the optimal solution across all operating environments in comparison with the construction heuristic.
Dedicated to my wife Sharita and children Taylor, Seth, and Nicholas
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Though the years in the doctoral program went swiftly by, there are many people who contributed to the completion of this dissertation. First, I would like to thank my advisor Bill Berry who has been steadfast in his support and unwavering in his request for excellence. Bill Berry was not only an advisor but also an example of what both professionalism and scholarship lead to when blended together. His ability to take my knowledge of process industries and mold it into a research topic is woven throughout this dissertation.

I would like to thank Dave Schilling who was a committee member since the beginning of this journey. Dave’s assistance in the analytical models presented in this dissertation and his ability to answer questions and return messages at the speed of light assisted in moving the dissertation along when I seemed to have come to a fork in the road. I would also like to thank Keong Leong who shared many of his evening hours with me when he was already exhausted. Keong’s guidance during the interview process gave me confidence and encouragement throughout my last year.

To the many doctoral students who came before me at The Ohio State University in the 90’s (you know who you are), thanks for all the support and phone calls. And to my fellow students in the program now, stay focused!
Finally, to my wife and soul mate, you are the spokes that helped keep the wheels rolling. Everything that comes out of this I owe to you yesterday, today, and tomorrow.

_The man who thinks he can._
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CHAPTER 1
INTRODUCTION

1.1 Purpose of research

This dissertation is concerned with developing affective heuristics for Master Production Scheduling (MPS) which improve performance with respect to both productivity and delivery in a single stage sequence dependent make to stock process industry environment. Productivity is defined in terms of reducing the total amount of changeover time in a schedule, and delivery as the length of time MPS orders are either early or late (i.e. order lateness). Despite the apparent practical importance of the problem, little work has appeared on Master Production Scheduling in the presence of sequence dependent changeovers with bi-criteria.

1.2 Problem Statement

Increased competition and rapidly changing environments has placed a tremendous amount of pressure on companies to improve manufacturing performance in process industries. Many changes have occurred in the areas of higher product quality, lower prices, and better responsiveness in terms of flexibility and customization (Slompak and
Nyland 1995). The seemingly conflicting goals of lower Production cost and meeting customer delivery dates are difficult to resolve in many firms.

Supporting these requirements is especially difficult for industries that have significant changeover cost, and which use batch processes, such as paper mills and chemical plants. They frequently schedule capacity first before raw materials. Price is an important competitive factor, and thus, operating at low cost is a top priority for these industries. This requires careful planning and close monitoring of production activities. These issues of meeting customer demands (delivery performance) and controlling production cost (productivity) is a difficult problem for process industry firms.

One aspect of efforts to improve productivity has been the development of an affective Manufacturing Planning and Control (MPC) system. MPC includes several interrelated modules and the Master Production Scheduling module is a key one among them. The function of the Master Production Schedule is to balance the product demands of customers with the supply of products made available by plant schedules and inventory. It specifies the timing and quantities of all end products to be produced. The MPS answers the 'what', 'when', and 'how many' to produce questions that are important in meeting customer expectations. It also provides the basis for key inter-functional trade-offs involved in the manufacturing planning and control process. The Master Production Schedule plays a major role by providing the key linkage between the front end production plans and the back end shop floor control systems. Because of capacity limitations the Master Production Schedule may in fact not be feasible when considering productivity and delivery performance criteria. The question here is how do we best design the Master
Production Schedule to minimize both changeover time and lateness while considering capacity limitations? Previous research on Master Production Scheduling has not addressed this problem.

One of the major concerns of process industry firms is the cost and length of product changeovers on batch processors. A changeover involves setting up a processor to produce a different product. An unusual aspect of many process industry firms with changeovers is that the changeover times are sequence dependent. That is, the processing of each job on the processor is preceded by a changeover whose duration depends on the immediate predecessor job. The problem of finding a schedule for producing products on a single processor with sequence dependent changeovers such that finding the minimum changeover time and lateness time is a difficult combinatorial problem.

A batch process produces several products, but only one at a time. In the beverage industry, for instance, considerable production time can be lost from the result of product changeovers which involves changing large amounts of fructose, and performing thorough rinsing to clean the impurities which may contaminate the next product scheduled on the processor. Conventional ways of making up the production loss, such as overtime or adding extra shifts, may not be possible as processors are scheduled 24 hours a day, 7 days a week.

For process industries with sequence dependent changeovers, changeover time is minimized by rearranging the product sequence, thus re-aligning their scheduled due date. This can cause products to be completed either early or tardy. In these cases it is
important that good scheduling techniques are used to minimize changeover time and lateness.

1.3 Production scheduling

Production scheduling has been the topic of numerous studies over the last five decades and continues to be a subject of extensive research. Scheduling is concerned with deciding how much of each product should be made and determining the order in which the products should be made. It involves determining the right timing of production such that the optimum trade-off between productivity and delivery performance is obtained. Process industries that have significant changeover times such as paper mills and chemical processing plants can lead to difficult scheduling problems. These industries may try to avoid product changeovers by scheduling long production runs, but such strategy can result in high inventory in some products and shortages in other products. The purpose of this research is to examine the tradeoffs between productivity (i.e. changeover time) and delivery performance (i.e. order lateness) under different operating conditions, determine operating conditions which effect performance and test three scheduling heuristics against the Master Production Schedule.

The problem of sequencing jobs to minimize changeover time can be formulated as a variation of the traveling salesman problem. Since the traveling salesman problem can be effectively optimized for only a small number of jobs, heuristic rules have been proposed to arrive at near optimal solutions (Gavett 1965, Haynes et.al 1973, White et. al. 1977, Guinet 1993). Thus one of the goals of this dissertation is to identify affective
heuristics (affective defined as quality of solution) that can solve relatively large bi-criteria sequence dependent scheduling problems.

1.4 Bi-criteria scheduling

Development of heuristics in which a single objective function is optimized has received considerable attention in the literature (Fry et.al. 1989, Nagar et.al. 1992). Frequently, production scheduling involves multiple goals. Hence multi-objective methods are operationally more meaningful and can provide the practitioner with alternate solutions and trade-offs among the various objectives.

Real life scheduling problems frequently require the decision maker to consider a number of criteria before arriving at a decision such as capacity, inventory, delivery, and productivity. A solution is optimal with respect to one criteria might be a poor candidate for another. The trade-offs involved in considering several different criteria provide useful insights to the decision maker. Thus considering problems with more than one criteria is highly relevant in the context of real life scheduling problems. Research in this important area has been scarce when compared to research in single criteria scheduling. (Dileepan and Sen 1988) list only sixteen papers in their survey paper on bi-criteria scheduling. A similar study undertaken by (Fry et.al. 1989) yielded thirty-two papers while (Nagar et.al. 1995) extended this work. None of these papers considered sequence dependent changeovers. This work will add to this scarce body of literature on bi-criteria sequence dependent scheduling.
1.5 Variables in production scheduling

This research considers a single stage, bi-criteria sequence dependent scheduling process. Factors need to be considered that effect performance of scheduling heuristics when applied to a Master Production Schedule for this process. Based on prior research (Haynes et al. 1973, Guinet 1977, Gupta and Darrow 1986) on sequence dependent scheduling, and empirical data collected from a process industry firm two factors are being considered in this study. These authors demonstrated that significant improvements in reducing changeover time can be accomplished by applying well designed heuristics. These reductions depend on system parameters, including the variance of the changeover times and the number of jobs to be sequenced (problem size).

Several different measurements have been used in the bi-criteria scheduling literature that considers productivity as well as delivery (Rubin and Ragatz 1995, Lee et al. 1997). These include tardiness, earliness and lateness measurements to capture delivery performance and minimizing changeover time to capture productivity performance. The performance measurement chosen for delivery in this dissertation is order lateness. This measures the ability of the Master Production Schedule to exactly meet the due dates. Lateness has been used in the bi-criteria scheduling literature and is useful in practice as it considers both early, and tardy completion of orders (Sen et al. 1988). An example problem will further demonstrate the dynamics of this problem.
1.6 Example problem

In this dissertation the focus will be on increasing productivity (i.e. minimizing changeover time) and meeting delivery dates (i.e. minimizing lateness) specified by the Master Production Schedule in a single stage make to stock process industry environment with sequence dependent changeovers. Though this may be a simplification of any specific real problem, it is a sufficiently valid representation of a class of problems to enable meaningful conclusions to be drawn from this research. The methods proposed in this research are suitable for solving the bi-criteria sequence dependent scheduling problem. To facilitate the discussion, these issues are illustrated using an example involving a process industry firm.

The example firm has a batch processor that produces ten different products. Forecasts are received from sales that initiate decisions to be made in Master Production scheduling. A Master Production Schedule is devised to ensure that forecast demand and inventory requirements are met. Every order in the Master Production Schedule has an associated MPS due date (See Table 1.1). Assume that production orders are scheduled using Master Production scheduling logic to determine the timing of individual orders. The changeover matrix for the ordered product pairs and the initial schedule are shown in Table 1.2. We assume that the last product for any given sequence is on the machine when production begins. For example in Table 1.2 changeover time would actually begin with a changeover from product 1 to product 1 which in this case equals zero. If we follow this
logic total changeover time equals 118 hours. Lateness in this dissertation is measured by summing over all orders the absolute value of the difference between the actual completion dates and due dates. For our example total lateness equals 79 hours. This is shown via an example (see Table 1.3).

Much of the previous research has only taken into consideration a single criteria in evaluating schedules. This example problem provides a clear view of the problem faced when only one criteria is considered.

Suppose that the objective is to improve productivity (i.e. reduce changeover time) in this example. One way to do so is to reduce the amount of changeover time in the schedule. A simple local swap heuristic will be used for illustration. The heuristic chosen in this example was adopted from the Clark and Wright Lockset heuristic (1962). The Lockset heuristic is a local search heuristic which has proved to be very efficient and has been tested extensively in vehicle scheduling. The heuristic has been tested in previous production scheduling research and produced schedules between 5% to 12% of the optimum schedule (Berry et.al 1999).

This heuristic is considered an improvement heuristic since it begins with the initial MPS sequence and attempts to reduce the changeover time through a series of local two way swaps of adjacent orders until no further improvement is possible. It is important to note that an improvement in changeover time is not always accompanied by an improvement in lateness. Consider the final schedule determined by the local SWAP heuristic after applying local pairwise swaps of adjacent orders shown in Table 1.4. A final schedule has total changeover time of 74 hours and total lateness of 309 hours. This final
lateness by 230 hours with respect to the initial MPS. This example demonstrates the problem of Master Production Scheduling in a sequence dependent environment when considering only one criteria.

From this example we clearly see that Master Production Scheduling in process industries is a difficult combinatorial problem. MPS orders have to be scheduled in order to meet the different objectives of minimizing both changeover time and lateness. The resource requirements (changeover time) of each task has to be considered, as well as the due date for each task to be scheduled. Undesirable outcomes such as increased changeover time, excess inventory, and shortages can arise when product completion dates are changed to minimize either objective of changeover time or lateness. This leads to a need for Master Production scheduling methods that consider bi-criteria. This research will address this problem by designing heuristics that consider both goals of changeover time reduction and lateness reduction, and provide an improved schedule compared to the Master Production Schedule.

1.7 Research questions

In order to study the central issue of minimizing changeover time and lateness it is necessary to address the following research questions. First, what is the relative performance of different scheduling heuristics with respect to minimizing changeover time and lateness? Because of the pressures in process industries to reduce changeover time productivity is often a major concern. Pressure from customers to increase delivery reliability and pressures to reduce inventory holding cost are also often a major priority.
Both need to be addressed when discussing how to effectively develop the Master Production Schedule for process industries. Second, what are the significant factors that impact changeover time and lateness performance when scheduling in process industries. Third, do certain heuristics outperform others under certain operating conditions? Likewise, how are these improvements affected by changes in these conditions? Previous research has shown that the scheduling environment (i.e. operating conditions) can effect the performance of changeover time reduction (Gavett 1966, Haynes et.al 1973). The affect of operating conditions may well be different for different heuristic procedures. This research examines the impact of different heuristic methods under different operating characteristics (i.e. coefficient of variation of changeover matrix, problem size) and a decision variable (trade-off parameter).

1.8 Contribution of research

This research addresses one of the major issues in sequence dependent Master Production scheduling, the ability to consider bi-criteria in the Master Production Schedule. The results of this research can help to improve productivity and delivery performance. These insights will include answers to the following research questions: What is the nature of the trade off between minimizing changeover time and lateness? What heuristic method should be used, and under what operating conditions? Does the number of orders (problem size) have an effect on performance (i.e. changeover time and lateness)? The key contributions of this study are as follows:
1. Development of bi-criteria heuristic methods for sequence dependent scheduling in single stage process industries involving changeover time and lateness.

2. Comparison of alternate methods of sequence dependent scheduling in process industries, considering changeover time and lateness.

3. Important operating factors that can effect performance of scheduling in sequence dependent operations using changeover time and lateness criteria will be examined along with their interactions.

1.9 Summary

This research provides a means for analyzing changeover time and lateness in single stage process industries with sequence dependent changeovers. The significance of this effort can be realized, by recognizing the fact that there has been very little prior research reported on Master Production Scheduling with bi-criteria and sequence dependent changeovers. This study will be useful to firms with large investments in process technology, helping them to understand the nature and form of managing changeover time and lateness. The results will provide managers with an understanding of which operating conditions effect the performance of changeover time and lateness. This framework will also provide a tool that will explain the tradeoffs between changeover time and lateness.
1.10 An outline of the dissertation

This chapter provides an introduction to the research problem being examined in this dissertation. Sequence dependent scheduling with changeover time and lateness criteria was identified as a major problem in process industry firms. Bi-criteria heuristics was identified as a viable approach to help solve this problem. The purpose of this research was defined, the major research issues examined, and the contributions of the study were discussed.

The second chapter reviews the existing research on bi-criteria scheduling with sequence dependent changeovers. Also, an exhaustive review of single criteria sequence dependent scheduling is also presented along with a review of the Master Production Scheduling literature. This chapter concludes with a summary of the research findings that are directly relevant to this research.

Different methods for solving the research problem are presented in the third chapter. Specific research questions and the hypotheses to be tested are discussed in chapter four. It discusses the measurements used in the experiments, and the rationale for choosing a simulation based research methodology. This chapter also includes a description of the experimental design, the factors and their levels, and the experimental procedure.

The data analysis and a discussion of the results are presented in chapter five. The evidence in support of the specific hypotheses set forth in the fourth chapter are examined for statistical significance. The statistical results and their managerial implications are
interpreted and presented. Chapter six summarizes the research findings with the emphasis on the contribution made by the research findings. It also identifies avenues for further research and outlines a framework for future research on Master Production Scheduling with bi-criteria and sequence dependent changeovers.
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Table 1.1 MPS orders and corresponding due dates

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Table 1.2 Product changeover matrix
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<td>88</td>
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Note: Total changeover time = 118 hours
Total lateness time = \( \sum |earliness| + \sum |tardiness| = 52 + 27 = 79 \) hours

Table 1.3 Calculating changeover time and lateness for initial MPS schedule

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</table>

Note: Total changeover time = 74 hours
Total lateness time = \( \sum |earliness| + \sum |tardiness| = 271 + 38 = 309 \) hours

Table 1.4 Calculating changeover time and lateness for heuristic schedule
CHAPTER 2

LITERATURE REVIEW

The topic of Master Production Scheduling in manufacturing firms has been recognized only in the past decade as an important topic area for research. As a result, very little research currently exists that focuses directly on Master Production Scheduling in process industries. This chapter begins by reviewing the literature that is related to the problem of bi-criteria Master Production scheduling with sequence dependent changeovers. This is accomplished by: (1) classifying the scheduling literature within a typology of production scheduling problems; (2) referencing selected Master Production scheduling articles that are relevant to this study; (3) referencing selected scheduling papers that has been reported on the problem of scheduling under sequence dependent changeovers; and (4) discussing selected articles that have been published on the problem of bi-criteria scheduling. We will first examine the relevant literature in Master Production scheduling, then introduce the sequence dependent scheduling literature and conclude with bi-criteria scheduling.
2.1 Classification of production scheduling problem

The scheduling literature has grown substantially in the last four decades. The scheduling literature includes several bibliographical and review works, including: (Moore and Wilson 1967, Bakshi and Arora 1969, Day and Hottenstein 1970, Godin 1978), and the textual works of Conway et.al. (1967) and Baker (1974).

Scheduling problems may be classified according to various schemes. Eilon (1979) has provided an excellent overview of several classification schemes. He has identified four important dimensions of scheduling problems which includes types of production, objectives, constraints, and decision variables. According to Eilon (1979), the scheduling problems can be classified as static vs. dynamic, deterministic vs. stochastic, single product vs. multiproduct, single period vs. multiperiod, and single machine vs. multiple machines. Though this is an excellent classification scheme used by Eilon (1979) one important dimension not included was whether changeovers between products are sequence dependent or sequence independent. This dimension is important in process industries because of the enormous pressure to reduce changeover time. This dissertation can be classified as a single machine, static, deterministic, sequence dependent, bi-criteria, scheduling problem. It is worth noting that we are considering process industries which is a vast departure from job shop scheduling. The intent of this literature review is to indicate the relevant literature in single stage bi-criteria Master Production scheduling with sequence dependent changeovers. Other issues concerning the effect of different operating conditions on performance and the performance measures involved in scheduling with bi-
criteria and sequence dependent changeovers will be discussed and will provide the foundation for the design of this dissertation.

We begin our review with a discussion on Master Production scheduling. As there are a number of papers in this category, a further sub-classification based on criteria used in the model and the environment under which these model operate will help to focus the literature even further.

2.2 Master production scheduling

Previous research in the area of Master Production scheduling has considered many different operating environments. Since this dissertation is concerned with make-to-stock environments we will consider only selected articles which study Master Production scheduling in make-to-stock environments.

Sridharan et al. (1988) consider the problem of measuring MPS stability, and the impact on stability of three important decision variables: the method used to freeze the MPS, the proportion of the MPS frozen, and the length of the planning horizon for the MPS. Simulation experiments were conducted to determine the impact of these decision variables. The results indicate MPS stability can be influenced by the proportion of the MPS frozen. The proportion of the planning horizon frozen should exceed 50 percent; but this will result in an increase in cost. The results also indicate that the period-based freezing method produces far less stable schedules relative to the order-based freezing method.

Lin and Krajewski (1992) use an analytical approach to study the Master Production scheduling problem in uncertain environments without capacity constraints.
The cost performance of an MPS depends on three decision variables: the choice of the replanning interval, which determines how often the MPS should be replanned; the choice of the frozen interval, which determines how many periods the MPS should be frozen; and the choice of the forecast window, which is the time interval over which the MPS is determined using newly updated forecast data. The effects of these decision variables on system costs, which include the forecast error, MPS change cost, setup, and inventory holding costs are explored. Results from the analytical model indicated that changes in environmental factors can cause a change in the best values for the decision variables.

The analytical model was tested against a simulation model and results indicated that the best combination of decision variables from the MPS model matched the best combination from the simulation model in 15 out of 16 environments. Total cost differences were within 1.0 percent in all 16 environments. Thus the authors conclude that there MPS model is a useful tool for MPS system design.

Zhao and Lee (1993) also reported results of a simulation study that addressed the relationship between the length of the MPS frozen interval and overall system performance given demand uncertainty. The dependent variables used to evaluate performance are total cost, schedule instability and service level. Their findings supported work done by Sridharan et.al. (1988). For example they found that a longer frozen interval improves schedule stability but results in a higher total cost and a lower service level. Zhao and Lee (1993) suggested that future work must incorporate capacity constraints as they are expected to have a significant impact upon their conclusions.
Kern and Wei (1996) conducted simulation experiments to explore the performance of rescheduling policies in capacity-constrained make-to-stock environments. Five research factors were examine including: degree of demand variation; forecasting model; capacity level; time fence scenario; and loading method. Three performance measures were analyzed: average finished goods inventory, total units of sales lost, and a measure of schedule instability. Kern and Wei (1996) concluded that level loading was the most robust loading method in that it provided the most consistent performance across environmental factors studied. Capacity level was found to be a significant factor in system performance. The results show that capacity exerts strong influence on the performance of the rescheduling methods investigated in the study. Higher levels of demand variation lead to degradation of system performance.

In summary, previous research on the issue of MPS in make-to-stock environments tend to focus on exploring the interrelationship among the freeze interval length, choice of planning horizon, demand variation, forecast methods, the selection of the forecast window and in some cases capacity constraints.

2.3 Sequence dependent changeover

The problem of sequencing jobs with sequence dependent changeover times has been analyzed by researchers for the last three decades. Subsequently, prior research will be classified based on criteria used as well as the solution methodology adopted to analyze the problem and single machine versus multiple machines. In accordance with this
dissertation there will be two criteria discussed in this section: (1) changeover time reduction; (2) meeting due date constraints. Solution methodology will be classified as traditional, which includes established techniques such as branch and bound and dynamic programming, while recent techniques include heuristic techniques such as simulated annealing, tabu search and genetic algorithms. A review of other issues related to sequence dependent scheduling, such as, the effect of operating conditions on performance and the performance measures involved will be discussed and will help to provide the foundation for the design of this dissertation.

2.3.1 Single machine sequence dependent scheduling with changeover time criteria

The sequence dependent changeover literature can be traced to Gavett's (1965) work where he presents the performance of three heuristics for sequencing jobs on a single machine with sequence dependent changeover. The objective of the sequencing decision is to minimize the changeover time over a finite number of orders. The experimental design considers three factors: (1) variance of the changeover time matrix; (2) the form of the distribution of the changeover time matrix; and (3) the number of orders in the sequence (problem size). There were four levels of the variance of the changeover time matrix ranging from .1 to .4, two forms of distribution, uniform and normal, and four levels of problem size 5 to 20. The performance measures used were % over optimum solution and performance against a random sequence.
The results indicate that the scheduling heuristics are a significant improvement over random sequencing. The average reduction in changeover time was 26% while the heuristics averaged 10% over the optimum solution. Reduction in changeover time depends on the environmental factors, including the type of distribution of the changeover matrix, the variance of the changeover time matrix, and the number of orders in the sequence. The results show that as the variance of the changeover time matrix increases the performance of the heuristics relative to the optimum solution on changeover time decreases. The results also indicate that performance relative to the optimum solution declines as problem size increases. The heuristics were closer to the optimum when changeovers were generated from a normal distribution compared to when changeovers were generated from a uniform distribution.

Haynes, Komar and Byrd (1973) extended the work of Gavett (1965) experimentally investigating whether one of the heuristic rules performs better relative to the optimum solution for a given number of orders and a particular distribution of changeover time matrices. The performance criteria is to minimize changeover time. Changeover time matrices were generated from normal, uniform, and gamma distributions for orders of 5, 7, 9, and 11. Changeover times obtained by the different rules for a specific order size were compared to the optimum solution and expressed as the percent error. The results show that the heuristic rule, order size, and the interaction of changeover time distribution with order size is significant at the $p = .05$. The effect of changeover time distribution is significant at a $p = .10$. 

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Barnes and Vanston (1980) discuss the problem of minimizing total changeover time and linear delay penalties when \( N \) orders, arriving at time zero are to be scheduled on a single machine. There are three levels of order size, 10, 15, and 20. The delay penalty for each order is a non-decreasing linear function of the sum of the various processing times for preceding orders, i.e., it is based on the delay induced past the start time. The authors discuss the application of several branch and bound algorithms using various branching rules. A hybrid dynamic programming algorithm is also utilized. This technique, detailed in the paper, applies a fathoming criterion to the states of the dynamic program in order to drastically reduce memory and computational requirements. Results are reported for a set of randomly generated problems that endorse the effectiveness of the hybrid approach over pure branch and bound methods in yielding confirmed optimal solutions. The performance measurement used was the average deviation from the optimal solution. The average percentage deviations from the optimal solution for the hybrid dynamic programming routine was 2.49% averaged over all problem sizes. The authors found the hybrid dynamic programming approach to be favorable because the branch and bound program failed to terminate in all but one case for the 20 order problems.

Driscoll and Emmons (1977) discuss the problem of minimizing changeover time while meeting demand. An efficient backward-time search procedure was used to solve the problem. The performance measurement was computer time, and storage capacity. Results indicate that the computational time increases rapidly with the number of orders
scheduled. However, there is a linear rate of growth of computer time with an increase in the number of customer orders for a constant number of products.

White and Wilson (1977) develop a procedure that classifies operations and predicts the changeover times. The authors also develop a method for sequencing orders to minimize total changeover time. White and Wilson use self-recorded changeover times from actual operating data, a changeover time operation classification scheme, and the statistical technique of multiple classification analysis to develop an estimation tool for sequence dependent changeover times. Multiple classification analysis is the same as a regression model using one explanatory variable for each level of each factor. After the orders are classified a heuristic method is used to minimize total changeover time. The heuristic operates very much like Sawiki’s (1973) where the total class of orders is sequenced with the stipulation that once a class is identified for processing no order outside that class will be processed until all orders in the class are completed. The performance measurement used is a comparison to Gavett’s (1965) heuristics. White and Wilson’s (1977) heuristic finds the optimal solution using the classification information whereas Gavett’s (1965) heuristic (next best after column deductions) finds the optimal solution but requires that the full Table of changeover times be available. The results demonstrate the methodology is an effective and inexpensive way to develop changeover time prediction equations which reflect the sequence dependency nature of many plants.

Lockett and Muhlemann (1972) consider a problem of scheduling orders on a machine using various machine tools in which considerable changing of the tools is
necessary and the setup times is sequence dependent. The objective is to minimize the number of tool changes i.e., setups. The authors derive a branch and bound algorithm which is shown to be computationally restrictive. Five heuristic methods were tried and showed promising results. The NB rule as mentioned above, the Travelling salesman without backtracking (where the first feasible solution obtained by branching is taken as the ordering for the jobs), Random ordering, Optimum travelling salesman, and The closest unvisited city. Results show that no solutions were obtained because a limit of 30 minutes was applied to each computer run. The ‘best’ heuristic measured by the number of standard deviations from the mean was travelling salesman without backtracking.

2.3.2 Single machine sequence dependent scheduling with tardiness criteria

Rubin and Ragatz (1995) introduce the application of a genetic search routine to solving the single machine problem. Instead of the normal objective function of minimizing makespan, the authors minimize the total tardiness of all jobs. The authors used a 2 x 2 x 2 experimental design. The factor were: (1) processing time variance, with two levels low or high; (2) tardiness factor with two levels low or moderate. The tardiness factor is roughly equivalent to the expected percentage of jobs in a randomly generated sequence that would be tardy; (3) range of due dates, with two levels narrow or wide. Each experimental design was ran at four levels of problem size (15, 25, 35, 45).
The results are very intriguing in that processing time is not a determinant of performance. When the due date range is wide, the genetic search technique produces good solutions faster than does the branch and bound procedure. When the due date range is narrow branch and bound is superior to genetic search. When tardiness is set at low and due date range wide, the problem is simple and both techniques locate an optimal schedule quickly. When the tardiness factor is set to moderate and the due date range is narrow neither genetic search nor branch and bound appears to be consistently superior.

Lee et al. (1997) propose a three-phase heuristic for the problem of minimizing total weighted tardiness. In the first phase three factors are computed in order to characterize the instance. The first factor is the due date tightness factor \( r \), the second factor is the due date range factor \( R \), and the third factor is the changeover time severity, where \( n \) is defined as \( n = s/p \) where \( s \) is the average changeover time and \( p \) is the run time. The second phase constructs a schedule by using the Apparent Tardiness Cost with setups (ATCS) rule, which has two parameters whose values depend on the results of phase one. The third phase consists of a post-processing procedure designed to improve the solution obtained by the second phase. Modifications to the schedule can be made in a number of different ways such as through an insertion or through a swap.

Lee (1997) rule is compared to an initial schedule that is randomly generated and is on the average better by more than 30%. It is observed that considerable improvement from the initial schedule can be achieved when due dates are relatively loose. When due dates are relatively tight it is harder to get a significant improvement. Results also indicate
that more improvement in changeover time is generated when the changeover to runtime ratio is relatively large.

Sawicki (1973) deals with scheduling orders of different classes on a production line with sequence dependent changeovers between classes. The changeover class specifies which category of changeover is required to begin servicing the order. The main objective is to minimize mean tardiness, though the standard deviation and maximum tardiness are also considered. Sawicki models an actual industrial facility where actual data was used to determine the characteristics of the distributions. A stream of data was then generated to closely resemble the available data.

In scheduling in this type environment Sawicki defines two levels of scheduling, first there are scheduling rules within a class (primary rule), and the second involves scheduling between classes (secondary rule). Sawicki defines the class exhaustion rule (primary rule) as: choose the next order from the same class as the previous order, if such a order exists, another class is chosen ‘only’ when the current class has been exhausted. Sawicki goes further and defines a primary rule which can be used for more than two classes, and with any specified fixed sequence. The basic idea behind this rule (the K primary rule) is to limit changeovers by establishing a minimum amount of processing time to be accumulated before allowing a class switch. K represents the value used in calculating the processing time requirements. When scheduling between classes (secondary rule) the rule is to choose the class containing the order with the smallest due-date.
The performance measurements used to determine the effectiveness of these rules is mean tardiness, standard deviation of tardiness, maximum tardiness, and the number of tardy orders. The class exhaustion rule with a fixed sequence is measured against using the parameter \( k \) with a fixed sequence (FCFS) and the parameter \( k \) with the minimum due date sequence. This fixed sequence is the FCFS (first-come, first-served). The fixed sequence rule exhausts each class on a FCFS basis, and progresses through the classes according to a sequence which is given by the solution of the traveling salesman problem for the changeover time matrix. The results indicate that in reference to the tardiness measures, the \( K \) rule can provide some improvement over the class exhaustion rule when operating with either the FCFS sequence or the minimum due date sequence. It also appears that there is a most favorable \( k \) value above and below which performance deteriorates. The results indicate that when scheduling between classes a single class does not necessarily need be exhausted before switching to another class.

Parthasarathy and Rajendran (1997) evaluate heuristics for scheduling on a single machine with sequence dependent changeovers to minimize the maximum weighted tardiness of orders. The authors present a heuristic that makes use of Simulated Annealing Technique (SA). Performance measurements considered were mean percentage deviation of a heuristic solution from the best heuristic solution, and mean absolute percentage deviation of a heuristic solution from the optimal solution. Three different order sizes were used to evaluate performance (8, 25, 95) along with three types of orders, namely high
priority, medium priority, and low priority, with relative weights as 3, 2, and 1 respectively. These weights are governed by the customer priority.

The results of the SA technique were compared against heuristics developed by Kim (1993) and Gelders and Sambandam (1978). The heuristic developed by Kim (1993) is a tabu search procedure which seeks to minimize mean tardiness of orders in a static flowshop. The heuristic by Gelders and Sambandam (1978) also minimizes the mean tardiness of orders in a static flowshop. The results indicate that the SA technique performs better than the existing heuristics when compared to the optimal solution across all operating environments for problem size of 8 orders. And SA has the smallest variance in tardiness for problem sizes of 25 and 95 orders.

2.3.3 Multiple machine sequence dependent scheduling with changeover time criteria

There is a small body of literature that considers scheduling with sequence dependent changeovers in processes having multiple stages and/or multiple machines. This literature differs from that discussed above in that there are multiple stages and/or multiple machines. Though this is not the same problem being considered in this research the results are worth noting.

Gupta (1982) presents a mathematical model based on the branch and bound technique to solve a static scheduling problem involving $n$ jobs and $m$ machines where the
objective is to minimize the cost (time) of setting up the machines. No intra-technique comparisons were made because of the unavailability of any other optimal or sub-optimal technique to solve such a problem. However, this algorithm can be used to solve small size problems.

Srikar and Ghosh (1986) solved the same problem as Gupta (1982). The difference was the model was a mixed integer linear program (MILP) formulation. This formulation has fewer number of variables and constraints as opposed to other Traveling Salesman like sequencing problems, though like all formulations of this type there are limitations on the size of the problem that can be handled. The authors test orders of size (3, 4, 5, 6). Each order size is tested at five levels of stages (2, 3, 4, 5, 6). The performance measures evaluated were mean CPU time and mean total nodes evaluated.

Results indicate that the mean CPU time increases as the number of orders increase and within each order size the mean CPU time increases as the number of stages increase. It can be noted from the results that solution times increase significantly with six orders relative to jobs of size one through five. It is also evident that problems with 4 or less stages, or 3 or less orders with up to 5 stages can be solved optimally.

Gupta and Darrow (1986) considers the static two-machine flowshop problem. Four heuristics were proposed to find approximate schedules for the problem and are empirically evaluated to assess their effectiveness in finding a minimum makespan schedule. Heuristic 1 & 2 are heuristics that use dominance conditions while heuristics 3 and 4 are local neighborhood search techniques. These algorithms were compared to the
optimum solution for small problems (up to 7 orders). The results were reported as percent error (percent above the optimum).

The results indicate that the neighborhood search technique averaged 0.7% over the optimum solution for problems up to 7 orders. For large problem sizes (30, 40, 50) the relative error was used as the performance measure. The relative error is defined as (makespan of the neighborhood search technique + makespan of heuristic j) where j is one of the 3 remaining heuristics. The results again pointed to the neighborhood search technique as the heuristic that provided better quality schedules. The heuristic outperformed the other three heuristics with respect to makespan in more than 50% of the cases.

Guinet (1993) considers the problem of scheduling sequence dependent products on identical parallel machines. The objective is to minimize the maximum completion time of the orders or the mean completion time of the orders. Guinet proposes an assignment heuristic to solve the problem. The heuristic is an extension of the Hungarian method to the multiple use of resources and has been developed to solve routing problems. There were six different levels of order size (25, 50, 75, 100, 125, 150) and four different levels of machines (3, 5, 7, 10). 1152 different problems were studied to evaluate the quality of the heuristic. The results were compared against a lower bound defined as (minimum $c(i,j) + p(j))$ from $j = 1$, N where N is the number of orders, M the number of machines, cij is the changeover time to process the job j directly after job i on the same machine and pj is the processing time of job j.
The results were very interesting in that the percent over the optimal solution declined as order size increased. This is contrary to the results found by Gavett (1965) and Haynes et al. (1973) and will be further investigated in this dissertation. Though within each order size the percent over the lower bound increased as the number of machines increased. The heuristic averaged 5.53% over the lower bound across all problem sizes.

De Matta and Guignard (1994) studied the effects of production loss during changeovers for process industries producing multiple products on non-identical flexible processors. The model is formulated to handle M machines and L processors (stages). The scheduling problem is formulated as a mixed integer programming model and solved using primal and dual Lagrangean based procedures. Actual operating data from a tile company and randomly generated data were used to test the model. Two factors were used in the experimental design: (1) planning horizon length in weeks (13, 26, 39, 52) and % production loss (0, 10, 20, 30). The dependent variable was changeover cost estimated as the product of production cost and unit manufacturing cost. The performance measurement considered was the % error defined as (Lagrangean solution - lower bound)/(lower bound).

The results indicates that total changeover cost decreases as planning horizons increase. This is with long planning horizons products can be produced ahead of their required due date to prevent congestion on processors during periods when large demands occur at the same time. Also, by producing ahead production loss can be recovered earlier which results in fewer changeovers and longer production runs.
2.4 Bi-criteria scheduling

As there are a large number of papers in this category, classification based on the criteria used in the model will define the literature directly related to this dissertation. Scheduling research involving more than one criteria will further be sub-classified under single machine bi-criteria problems (SMBP). The majority of research on the SMBP has considered the minimization of job flowtime as one of the objectives. Other criteria have often been due date oriented. All papers considered minimize a linear combination of the objective function except for Miyazaki (1981).

2.4.1 Single machine bi-criteria scheduling

Van Wassenhove and Gelders (1980) consider \( n \) jobs to be sequenced on a single machine. The objective functions to be minimized are flowtime and maximum tardiness. Minimum makespan is reached by ordering the jobs according to nondecreasing processing times and that maximum tardiness is reached by ordering the jobs according to nondecreasing due dates (EDD rule). The authors present a heuristic that first places jobs in SPT sequence then backwards schedules to minimize maximum tardiness. The heuristic was coded in Fortran and data randomly generated from a uniform distribution with \( 1 \leq p_i \leq 10 \) and \( 0 \leq d_i \leq \sum p_i \). The heuristics was tested at problem sizes of \( (10, 20, 30) \). The performance measurement considered was minimum CPU time. The results conclude that (a) a slight decrease in one objective function (flowtime) often results in a large decrease in the other (tardiness). (b) CPU times increase as problem size increases.
Van Wassenhove and Baker (1982) discuss a bi-criteria problem where the objective function is to minimize total processing time and total cost. A heuristic is designed that produces an efficient frontier of possible schedules. Weights are placed on both of the objectives and the heuristic finds the minimum value for the linear combination of cost and processing time. No performance measurement was reported just an example given on how the procedure works.

Sen and Gupta (1983) considers the problem of minimizing a linear combination of flow times and maximum tardiness of a given number of orders on a single machine and presents a branch and bound technique to arrive at an optimal solution. Factors used in the experimental design were \( p \) (weighting factor) \( p = .25, .50, .75 \), \( r \) (due date range), and \( n \) (order size) \( n = 5, 10, 15 \). The performance measurements reported was the average number of nodes generated and average CPU time in seconds. An analysis of the data reveals that problems with a small due date range are most difficult to solve in terms of average number of nodes and CPU time. This result is consistent with Rubin and Ragatz (1995) in that when due date ranges are narrow CPU times increases to find optimum solution relative to when due date ranges are wide. These observations are true for each combination of \( p \) and \( n \). Computational effort is found to be considerably less for a large value of \( p (p = 0.75) \), i.e., when total flowtime is more heavily weighted than maximum tardiness. For large \( n \), problems with equal weights tend to be the most difficult relative to CPU time.
Fry and Leong (1987) introduce two procedures for the single machine multiple objective problem. The objective was to minimize a linear combination of the two criteria considered (mean flowtime, and mean earliness). The problem was solved using a mixed integer linear programming formulation. Ten different problems were solved for problems of size 6, 8, 10, 12 and 14 jobs. Performance measurement used was CPU time in seconds. Results show that as problem size grows the computational requirements increase at an almost exponential rate.

Miyazaki (1981) considers a single machine bi-criteria problem with mean weighted flowtime and job tardiness as the two criteria. Miyazaki’s approach is different than papers mentioned above in that the objective is to minimize mean weighted flowtime with job tardiness as a constraint. A heuristic is developed that determines a local optimum. A tabu search is then used that consequently develops an improved schedule based on the locally optimal schedule. The performance measurement used was CPU time in seconds. The results show that as problem size grows the computation time increase also.

2.5 Summary of literature review

In this chapter we reviewed the existing literature on Master Production scheduling, sequence dependent scheduling and bi-criteria scheduling, concentrating on areas directly related to this dissertation. The major conclusions that emerge from this
review provide the foundation for the research design to study the single machine bi-criteria Master Production scheduling problem with sequence dependent changeovers.

- While the MPS literature (see Table 2.1) predominantly focuses on performance measures as schedule stability, lost sales, finished goods inventory, and service levels, there is no research that directly addresses issues concerning process industries. These include scheduling under sequence dependent changeovers where reducing changeover time and meeting customer orders are of high importance. In this dissertation we explore the use of scheduling heuristics in improving MPS performance in single stage make-to-stock environments with sequenced dependent changeovers.

- Several authors have recognized that bi-criteria scheduling is a key issue in industry which needs to be addressed. The same can be said for industries that have sequence dependent changeovers. Most of the bi-criteria work has been done with changeovers being independent of one another. A number of observations can be made from the discussion on bi-criteria scheduling including, 1) Bi-criteria problems with due dates as one of the criteria clearly demonstrate that a wide range of due dates lead to an easier problem to solve. 2) Most of the work in this area has been solved using branch and bound procedures and enumeration techniques trying to find optimum solutions. With these procedures only small problem sizes have been examined. Thus the need to design techniques that can solve larger problems 3) The weight placed on the objective function can be a dominant factor that can affect the computational time and the complexity of the problem i.e., the average number of nodes. For example the research was consistent in that
computation time is less when total flowtime is more heavily weighted. It should be noted here that none of these bi-criteria papers included sequenced dependent changeovers.

- Despite the proliferation of research on single machine scheduling, there is very little research on scheduling sequence dependent processes. Nearly all of the research has been carried out under the assumption that changeover times are sequence independent. Though the collection of articles in this area is small the conclusions drawn will help to build the foundation. These include the following; 1) Improvement in changeover time relative to the lower bound depends on the type of distribution of the changeover matrix, the variance of the changeover matrix, and the number of orders in the sequence. 2) Problem size and the interaction of problem size and the distribution of the changeover matrix is significant 3) The computation time increases rapidly with problem size. 4) Processing time is not a determinant of performance and 5) More improvement in changeover time is generated when the ratio of changeover time to processing time is relatively high.

- Most of the sequence dependent scheduling literature work can be categorized under the single criteria case. Very little work on sequenced dependent scheduling with bi-criteria. Barnes and Vanston (1981), Driscoll and Emmons (1977), and Sawicki (1973) are the only papers that have considered bi-criteria in their model. Of these three only Sawicki (1973) considers due dates as one of the criteria. The shortage of work in bi-criteria sequence dependent scheduling indicates the need to develop new methodologies to successfully deal with processes with sequence dependent changeovers.
• The criteria most often used by researchers considering sequence dependent changeovers seem to be related to job flowtime. Specifically, performance measures involving average, total, and weighted flowtime have been most commonly used. Tardiness based performance measures, such as, number of tardy jobs and maximum tardiness have been used sparingly in the literature. To provide a more realistic criterion to measure schedule performance, researchers have often used cost functions. These functions are usually in the form of penalties based on some performance characteristics. Little research has been found on lateness as a criteria. Lateness based performance measurements gives a good indication of how well the scheduling technique performs. In many production environments the concern is how well the schedule meets the due date. In many firms early orders are just as costly as tardy orders. Thus we feel the need to incorporate lateness as a criteria into our model.

• A major weakness of the scheduling research discussed in this chapter is the reliance on general combinatorial methodologies such as branch and bound, and dynamic programming. A major drawback of these techniques is the computation time requirement for larger problems. Many of the problems being considered cannot be solved when more than 20 orders are present. Clearly, this limits the applicability of most of the techniques mentioned above. In this work we look at problems with as many as 100 orders. Only a few papers have looked at problems of this size.

• Clearly one major drawback of the literature in this area is the lack of attention given to the impact of the operating characteristics on the effectiveness of the techniques
mentioned for solving the bi-criteria problem with sequence dependent changeovers. The most commonly used factors discussed have been product related, such as due date range. Here we focus on other factors such as variance of changeover.

This chapter provided the necessary theoretical foundation for investigating the bi-criteria Master Production scheduling problem with sequence dependent changeovers. In general we can conclude:

1. Implementing bi-criteria objectives into the decision making process is important because of the nature of the tradeoff between delivery (due date criteria) and cost (changeover time criteria). This can be an economically viable strategy for achieving high performance in terms of meeting customer expectations.

2. The cost / customer service trade-off needs to be studied under a variety of operating conditions; i.e., problem size, variance of changeover matrix, weighting factor placed on the criteria, and performance of different heuristics.

3. The bridging of these three literature streams: 1) Master Production scheduling; 2) sequenced dependent scheduling; and 3) bi-criteria scheduling, needs to be broadened because of the importance of the problem and the scarce amount of research in this area.

In the following chapters we first describe three different heuristic procedures that will be used in this dissertation. Then, the research design is discussed. Finally, the results, conclusions and future extensions are presented.
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**Table 2.1** Master Production Scheduling performance criteria
CHAPTER 3
RESEARCH METHODOLOGY

Master Production scheduling in process industries is a complex problem when changeover time and lateness are the two criteria. The output of a Master Production Schedule is a sequence of orders to be completed by a certain date in order to supply demands for customers orders or to replenish inventories. As demonstrated by the example in chapter 1 minimizing changeover time does not always minimize lateness. Early or tardy completion of orders can have many consequences including high inventory and shortages. Thus the question becomes how do sequence the Master Production Schedule to ensure that we minimize both changeover time and lateness given the relative importance of each objective? Some firms put more emphasis on minimizing changeover time where other firms emphasize lateness. This research investigates the problem of re-sequencing the Master Production Schedule of a single processor to minimize a weighted sum of changeover time and lateness where changeovers are sequence dependent.

In pursuit of solving this problem, the purpose of this chapter is to describe and demonstrate three heuristics that may be used to schedule MPS orders with changeover time and lateness criteria. These heuristics are Simulated Annealing, Minimum CO/L (Construction Heuristic), and Three-Opt. The three heuristic methods presented in this
chapter do not guarantee optimal solutions. However, they share the advantage of being computationally efficient on large problems. All three heuristics are designed to solve the research problem in its most general form. That is, they are designed to solve the problem of sequencing a set of MPS orders to minimize a weighted sum of changeover time and lateness. Though these heuristics are designed with the same purpose in mind they do differ in how they accomplish this task of sequencing.

Simulated annealing offers a powerful search heuristic for obtaining excellent solutions for large problems. Unlike local optimization or iterative improvement techniques, simulated annealing randomizes this procedure in a way that allows for occasional changes that worsen the solution, in an attempt to reduce the probability of becoming stuck in a locally optimal solution. The Construction heuristic starts with a set of orders and builds a sequence attempting to minimize the weighted sum of the objective function as orders are added to the sequence. Three-Opt is a global heuristic that seeks to improve the MPS sequence of orders by examining interchanges of three orders. The interchange is accomplished by reassigning the orders on either side of each changeover. This chapter is outlined as follows: First we formulate the problem and introduce all important variables. We then describe each heuristic in detail and illustrate the mechanics via the example shown in chapter 1. We end with conclusions and a summary.
3.1 Problem formulation

In order to derive an appropriate objective function to investigate the effect of minimizing changeover time and lateness, a tradeoff parameter $\omega$ will be used to combine the two criteria into a single objective function.

Suppose that there is a set of $n$ orders that are available for processing at time zero. Once processing starts on an order, it is completed before the next order is begun. Let $p$, $t$, and $d$ represent the process time, job completion time, and due date of job $j (j = 1, \ldots, n)$ respectively. $C(i, j)$ represents the changeover time to process job $j$ directly after job $i$. Then the lateness of job $j$, $L_j$, is defined as: $L_j = t_j - d_j$. If $F(S)$ and $G(S)$ represent the changeover time and degree of lateness for a particular schedule $S$, then

$$F(S) = \sum_{i=0}^{n-1} \sum_{j=1}^{n} (C(i, j)(S)) \quad \text{and} \quad G(S) = \sum_{j=1}^{n} \text{ABS}(L_j(S))$$

The trade-off parameter $\omega$ is the relative importance of changeover time and lateness, thus a decision maker can change $\omega$ depending on the relative importance of changeover time to be minimized in comparison to lateness. Hence, the problem becomes one of determining a schedule $S$ that minimizes the following objective function:

$$Z(S) = pF(S) + qG(S), \text{ where } p, q \geq 0, \quad p + q = 1$$

s.t $\quad F(S) \leq \text{CAP}$
It should be noted that in this environment, minimizing makespan is equivalent to minimizing changeover time since the total run times of all the orders remain the same regardless of the sequence.

One important issue in bi-criteria research is the normalization of the objective function. One option is to scale the objective function. Steuer (1986) suggests to scale the objective function only if the two criteria are not of the same order of magnitude. In our case changeover time and lateness are both of the same order of magnitude. Since we are comparing the heuristic schedule to the initial MPS we chose to normalize the objective function against the initial MPS by dividing both criteria by the initial MPS values. Thus the MPS is set equal to one.

In the following sections we will introduce three heuristics that will be used to re-sequence the Master Production Schedule. Each heuristic will be followed by an example problem.

3.2 Simulated Annealing heuristic

Simulated annealing (SA) is a randomized local search method that has been used to derive near optimal solutions for computationally complex optimization problems. It was originally developed as a simulation model for a physical annealing process (Metropolis 1953) and hence, the name “simulated annealing” has been used to describe the methodology. We can apply this methodology to Master Production scheduling by viewing it simply as an enhanced version of local optimization, in which the Master Production Schedule is repeatedly improved by applying a heuristic until no further
improvements can be made. The SA technique randomizes this procedure in a way to attempt to reduce the probability of getting stuck in a poor, but locally optimal solution. The simulated annealing methodology differs from local search methods since it allows some positive probability of accepting an inferior solution in a neighborhood when compared with the current best solution (referred to as the seed solution).

If \( C_s \) represents the changeover time of the initial Master Production Schedule (\( S \)) and \( C_s' \) represents the changeover time of a heuristics solution (\( S' \)), and we assume that \( S' \) is inferior to solution \( S \) (i.e., \( C_s > C_s' \)) then an acceptance probability function \( \exp(-\delta/T) \) where \( \delta = C_s' - C_s \) and \( T \) is a control parameter which corresponds to temperature or in this research a starting condition. This acceptance function has been applied in the literature extensively (Jeffcoat and Bulfin 1993, Zegordi et al. 1995, Daya and Al-Fawzan 1996, Parthasarathy and Rajendran 1997, Park and Kim 1998). The acceptance function implies that small increases in the objective function are more likely to be accepted than large increases, and that when \( T \) is high most moves will be accepted, but as \( T \) approaches zero most increases in objective functions will be rejected. So in SA, the algorithm is started with a relatively high value of \( T \), to avoid being prematurely trapped in a local optimum. The algorithm proceeds by attempting a certain number of exchanges of orders at each temperature, while the temperature parameter is gradually dropped.

Although the general approach to solving problems using simulated annealing is well known, the issues to be addressed in this dissertation requires careful consideration of ways to implement the simulated annealing approach. Specifically, simulated annealing requires generating a new sequence, specifying the probability of accepting a potential new
sequence and setting the values for parameters that control the scheduling process. These aspects of simulated annealing for this dissertation are discussed in the following paragraphs.

3.2.1 Setting the control parameters

A SA heuristic specifies the number of iterations \( x \), the number of "searches" to be carried out at each iteration \( y \), the acceptance probability \( AP_y \), the scheduling algorithm, and the termination rule. Although the simulated annealing procedure is guaranteed to converge to optimality, this usually requires a large number of iterations as well as a large number of searches at each iteration (Eglese 1990).

The three control parameters, the initial temperature \( T_0 \), the final temperature \( T_f \), and the temperature reduction factor \( r \) must be determined a priori before the simulated annealing scheme can be applied. Pilot runs of the research problem was used to derive a good estimate for these three parameters. The fundamental principle of simulated annealing is to allow an equal chance of rejecting or accepting a worse solution initially. This is achieved by slowly decreasing \( T_{max} \) to \( T_o \) at the rate of \( (1 - r) \) percent. In a method suggested by Van Laarhoven et.al. (1987), SA is stopped when the temperature drops down to a pre-selected final temperature \( T_o \). The next section discusses how we set the control parameter.
3.2.2 The initial temperature \( (T_i) \) and final temperature \( (T_o) \)

In Connolly's (1992) method, the initial and final temperatures were determined by information obtained in trials prior to the annealing process. In these trials, a certain number of random pairwise exchanges were performed on the initial MPS to record the resulting changes in the objective function. Previous research (Zegordi et al. 1995) has set the number of trial exchanges to 50 in determining the initial and final temperatures. From the results, the minimum value \( \Delta Z_{\text{min}} \) and the maximum value \( \Delta Z_{\text{max}} \) for the changes in the objective function were calculated for these exchanges. Using these values, the initial temperature \( T_i \) and the final temperature, \( T_o \), were set according to the following equations:

\[
T_i = \Delta f_{\text{max}} - \Delta f_{\text{min}},
\]

\[
T_o = \Delta f_{\text{min}}
\]

3.2.3 The temperature reduction factor

The temperature reduction factor, \( r \), should be as small as possible so as to provide a better probability for the annealing schedule to escape local optimum. However, the computation effort would be too long if \( r \) is too small. Parthasarathy and Rajendran (1997) used a temperature reduction factor of 0.90.

3.2.4 Random exchange scheme

A random exchange heuristic has been tested extensively in the scheduling literature (Huegler and Vasko 1997, Russell and Holsenback 1997) and found to produce
solutions averaging between 6% to 12% of the best known solutions. A generic procedure of the interchange heuristic is given below:

Step 1. Start with the schedule generated from the initial MPS and call this sequence $S$.

Step 2. Calculate the objective function value $Z$ for the initial MPS.

Step 2. Randomly generate two integer numbers from a uniform distribution between 1 and $n$, where $n$ is the number of orders in the MPS. Let these two random numbers represent the order numbers.

Step 3. Exchange the position of these two orders in the sequence and call this new sequence $S'$.

Step 4. Calculate the objective function value $Z'$ for the new sequence $S'$.

Now that we have defined the necessary parameters and solution variables for Simulated Annealing we now proceed to present a detailed description of the Simulated Annealing procedure.

3.2.5 Simulated Annealing algorithm

The simulated annealing algorithm is represented in general terms below:

Step 1. Obtain the initial MPS ($S$).

Step 2. Set the control parameters

Initial temp ($T_i$)
Final temp ($T_f$) at which the system is considered frozen
Temperature decay rate, ($r$)

Step 3. While not yet frozen perform the random exchange scheme.
Step 3.1 Apply the secondary algorithm, from which we get $S'$.

Step 3.1.1 Let $\Delta Z = Z' - Z$.

Step 3.1.2 If $\Delta Z \leq 0$, accept the new sequence.

Step 3.1.3 If $\Delta Z \geq 0$

(i) calculate the probability of accepting that change from the probability function $AP = \exp(-S/T)$

(ii) select $u$, a uniformly distributed random number between 0 and 1. If $(AP) > u$, accept the new sequence. If $(AP) \leq u$, reject the new sequence, and retain the previous sequence prior to step 3.1.1

Step 3.1.4 Return to step 3.1

Step 3.2 Set $(T) = r(T)$

Step 4. If $(T) = (T_0)$ go to step 5 else return $(S)$ and go to step 3.

Step 5. Stop

3.2.6 Example using Simulated Annealing

To illustrate how we can apply Simulated Annealing to improve the initial MPS refer to the example problem in Chapter 1 (See Tables 1.1 and 1.2). To illustrate this example we will set the trade-off parameter $\omega$, equal to .99. Thus the objective function value for the initial MPS schedule is the following:

Step 1. $Z(S) = (.99) \times 118 + (.01) \times 79 = 118$ hours

Step 2. Set the control parameters as follows:

$\Delta f_{min} = 4, \quad \Delta f_{max} = 306$

$T_i = \Delta f_{max} - \Delta f_{min} = 302$
\[ T_o = \Delta f_{min} = 4 \]

Step 3. Apply the random exchange heuristic to the initial Master Production Schedule. The first two randomly generated numbers were in position 4 and 2. Thus from exchanging these two orders the new schedule \( S' \) is (1-5-6-6-7-9-2-10-4-1). The new objective function value \( Z(S') = (.99) \ast 98 + (.01) \ast 211 = 99 \) hours (See Table 3.1).

\[ \Delta Z = Z' - Z = 99 - 118 = -19 \]

Since \( \Delta Z \leq 0 \), accept the new sequence \( S' \)

\[ S = S' \]

Step 4. \( T_i = .95 \ast 302 \)

Step 5. If \( (T_i) = (T_o) \) go to step 6 else return \( (S) \) and go to step 3.

Step 6. Stop

There are too many iterations in the simulated Annealing heuristic for one to list in the dissertation. The final solution was the same as the final solution in Chapter 1. Considering aspects of both solution quality and computational efforts, the following conclusions can be summarized from SA literature and validates the reasoning for choosing SA for this dissertation:

(1) For relatively small size problems, the proposed heuristic has good ability to reach optimum solutions, by using much lower CPU time (Vakharia and Chang 1990).

(2) For larger size problems (30-60 orders), the computational effort required for obtaining high quality solutions (within 2% error) is considerably less than other techniques.
3.3 Construction heuristic

The Construction heuristic outlined below was adopted from Gavett’s (1965) “Next Best” rule. The heuristic is designed to select the unassigned order which has the least changeover time relative to the order which has just been completed. This heuristic is designed to minimize at every decision point (a point where a new order is to be scheduled) the weighted sum of changeover time and lateness. The following is a detailed description of the Construction heuristic procedure.

**Variable Description**

S is the initial MPS schedule array  
D is the due date array of initial MPS  
S\_N is the new schedule array to be built  
D\_N is the new due date array for schedule S\_N  
i, j are indices for MPS schedule and new schedule S\_N  
CO is changeover time array  
D\_C is completion time array  
Z is array of objective function values

**Step 1.** Initialize due date array $D$, initial MPS schedule array $S$, new schedule array $S\_N$, and new due date array $D\_N$. $N$ equals the number of orders in set $S$.

**Step 2.** $S\_N(1) = S(1)$

**Step 3.** calculate the changeover time for the product on the processor and choose for the next product in $S\_N$ that which has the smallest objective function value.

Do $j = 1$, $n-1$

Do $i = 2$, $n$
\[ co(i) = (co(s_n(j), s(i))) \]
\[ D_C(i) = \text{ABS}(D(i) - co(i)) \]
\[ z(i) = (p*co(i)) + (q*d_c(i)) \]

End do

Step 4. Choose the smallest objective value from array Z to place in position i

Step 5. End Do

Step 6. Stop

3.3.1 Example using Construction heuristic

For example of the Construction heuristic we will use the same example from Chapter 1.

To illustrate this example we will set the trade-off parameter \( \omega \) equal to .99. Thus the objective function value for the initial MPS schedule is the following:

Step 1. \[ Z(S) = (.99) \times 118 + (.01) \times 79 = 118 \text{ hours} \]

Step 2. Set the order in position 1 of S_N to equal to the order in position 1 of the initial MPS. In this example this is product 1.

Step 2.1 Set \( j = 1, n - 1 \)

Step 3. Calculate the changeover time from order S_N(j) to every order in the initial MPS set. The order with the smallest objective function value is set to the position S_N(j+1). In our MPS example this is order number 10 which is product 1

Step 4. If \( j = n-1 \) go to step 6

Step 5. Else \( j = j + 1 \) and go to step 3

Step 6. Stop
If we complete these steps the Construction heuristic builds a different schedule from both 3-OPT and SA (See Table 3.2). With 99% of weight on reducing changeover time there are 4 more hours of changeover time with the Construction heuristic than for either 3-OPT or SA. Though the Construction heuristic has 10 less lateness hours than both 3-OPT and SA. In the next section we will give a detail description of the 3-OPT heuristic.

3.4 3-OPT heuristic

3-Opt is a global swap heuristic adapted from Lin and Kernighan’s (1973) routine that attempts to improve a traveling salesman route by interchanging three routes and examining the distance saved. This heuristic is being adopted in this research by applying the logic to a sequence dependent changeover matrix. The following is a detailed description and example of the 3-OPT procedure.

Step 1. Begin with the initial MPS set of orders (S) numbered sequentially, indexed from 1 to n, where n is the total number of orders as in chapter 1. Note: any reference in the steps below to an index which is larger than n is converted to an index between 1 and n. For example, a reference to index n + 2 would be implemented as a reference to the second order in the production sequence. Calculate the objective function value for the initial MPS: Z(MPS)

Step 2. For all \( i = 1, n \)
For all \( j = i + 2, n + i - 3 \)
For all \( k = j + 2, n + i - 1 \)
create a new schedule (S_N) as follows:
\[ i-1,i,j+1,j+2,\ldots,k-1,k,i+1,i+2,\ldots,j-1,j,k+1,k+2 \]
Step 3. Calculate the objective function value Z(S\_N).
If Z(S) < Z(MPS) then
   Z(MPS) = Z(S)
   (S) = (S\_N)
   Repeat step 2
else
   Repeat K
      Repeat J
         Repeat I
   END IF

Step 4. Stop. There are no further reductions of changeover times possible from
the interchanges considered.

The following is an example of the 3-OPT procedure using the data in Chapter 1.

3.4.1 Example using 3-OPT heuristic

Step 1. Start with the initial MPS sequence in chapter 1 of (1-5-6-4-7-9-2-10-6-1).
With orders numbered sequentially in a given schedule, let i, i+1, j, j+1, k,
k+1 represent three order changeovers, where j > i+1 and k > j+1.

Step 2. Create a new schedule: (1-4-7-5-6-9-2-10-6-1)

Step 3. Calculate the objective function value (see Table 3.3). In this example \( \omega = .99 \) thus the objective function value is:
\[ Z(S\_N) = .99 \times 122 + .01 \times 139 = 122. \] Since the objective function value of 122 is greater than the MPS objective function value of 118 we keep the initial MPS as sequence (S). Repeat k.

Step 4. Create a new schedule: (1-4-7-9-5-6-2-10-6-1)
Step 5. Calculate the objective function value (see Table 3.4). The objective function value is: \( Z(S_N) = 0.99 \times 114 + 0.01 \times 137 = 114 \); Since the objective function value is less than the MPS objective function value of 118 we exchange the orders and the new improved schedule becomes the MPS schedule (S). Repeat step 2. The 3-OPT routine goes on for several iterations. The final schedule is the same as the example in Chapter 1.

### 3.5 Conclusions

The three procedures described in this chapter provide a range of heuristics sufficient to answer the research questions. The Simulated Annealing Technique is a more recent technique applied to scheduling that has shown to give excellent results when scheduling in sequence dependent setup environments (Parthasarathy and Rajendran 1997). The Construction heuristic is a new heuristic developed specifically to solve this problem. It is unique from the other two in that it takes into account both criteria when building the schedule. Three-OPT has been tested extensively and has proven to find near optimal solutions when scheduling with sequence dependency. It is evident that the three heuristics characterized in the preceding sections have very different characteristics. It is necessary to examine each procedure under a variety of operating conditions to identify the performance differences between these three procedures. The next chapter outlines the specific research questions examined in this dissertation and also presents the experimental design used to examine the research questions.
<table>
<thead>
<tr>
<th>Heuristic Schedule</th>
<th>1</th>
<th>5</th>
<th>6</th>
<th>6</th>
<th>7</th>
<th>9</th>
<th>2</th>
<th>10</th>
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<td>100</td>
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<td>53</td>
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<td>88</td>
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<td>17</td>
<td>76</td>
<td>15</td>
<td>5</td>
<td>14</td>
<td>12</td>
<td>39</td>
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<tr>
<td>Tardiness</td>
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</tbody>
</table>

Note: Total changeover time = 98 hours
Total lateness time = $\Sigma |\text{earliness}| + \Sigma |\text{tardiness}| = 172 + 39 = 211$ hours

Table 3.1 Calculating changeover time and lateness for simulated annealing

<table>
<thead>
<tr>
<th>Heuristic Schedule</th>
<th>1</th>
<th>1</th>
<th>5</th>
<th>4</th>
<th>10</th>
<th>7</th>
<th>9</th>
<th>2</th>
<th>6</th>
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<td>29</td>
<td>47</td>
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<td>53</td>
<td>76</td>
<td>41</td>
<td>100</td>
</tr>
<tr>
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<td>13</td>
<td>3</td>
<td>12</td>
<td>33</td>
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<tr>
<td>Tardiness</td>
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</tbody>
</table>

Note: Total changeover time = 78 hours
Total lateness time = $\Sigma |\text{earliness}| + \Sigma |\text{tardiness}| = 266 + 33 = 299$ hours

Table 3.2 Calculating changeover time and lateness for construction heuristic
<table>
<thead>
<tr>
<th>Heuristic Schedule</th>
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<th>4</th>
<th>7</th>
<th>5</th>
<th>6</th>
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</tbody>
</table>

Note: Total changeover time = 122 hours
Total lateness time = $\sum |\text{earliness}| + \sum |\text{tardiness}| = 72 + 67 = 139$ hours

Table 3.3 Calculating changeover time and lateness for 3-OPT heuristic

<table>
<thead>
<tr>
<th>Heuristic Schedule</th>
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<th>4</th>
<th>7</th>
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<tr>
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</tbody>
</table>

Note: Total changeover time = 114 hours
Total lateness time = $\sum |\text{earliness}| + \sum |\text{tardiness}| = 97 + 40 = 137$ hours

Table 3.4 Calculating changeover time and lateness for 3-OPT heuristic
CHAPTER 4
EXPERIMENTAL DESIGN

Three procedures scheduling multiple MPS orders on a single processor with sequence dependent changeovers have been developed and described in chapter three; simulated annealing algorithm, a global swap heuristic (3-OPT) and a Construction heuristic. This chapter is concerned with the methodology that is used to evaluate and compare the operating performance of the scheduling procedures. The research methodology to compare these three heuristics is designed to provide insight into the following:

1. The relative advantage of one heuristic procedure over the other in terms of performance, and whether or not these results hold for all problems, or are dependent upon the characteristics of a particular problem defined by the operating conditions.

2. Which operating conditions have a major impact on performance when scheduling in this environment.
In the following section the research questions and hypotheses are presented followed by the rationale for choosing an experimental design. Then the experimental variables and experimental design are introduced. We then describe the statistical procedure employed to analyze the experimental data. We conclude with a summary.

4.1 Research questions and hypotheses

This research investigates four experimental factors. These factors are (1) Scheduling Heuristics, (2) Tradeoff parameter, (3) Problem size, (4) Coefficient of Variation. The research issues examined in this study are developed in two steps. In the first step the research questions are formulated and in the second step these research questions are translated into testable research hypotheses. These hypotheses provide the basis for examining the research issues raised, using appropriate statistical testing procedures. Two basic forms of questions are presented: a) research questions on the relative performance of alternate scheduling heuristics, and b) research questions pertaining to the impact of operating factors on performance. When all performance measures are mentioned we are referring to percent improvement in changeover time, percent improvement in lateness, and percent over optimal solution.

4.1.1 The affect of the trade-off parameter

In the formulation of the objective function, \( \omega \) was used to determine the tradeoff between the two objective functions, changeover time and lateness. When \( \omega \) is equal to 0.001 or .999 the problem becomes a single objective problem and with \( \omega \) equal 0.5 we
have a bi-criteria problem. Using a tradeoff parameter to increase or decrease the weight on either objective lends to the following questions?

1. Does solution quality change as the trade-off parameter increases?

2. Does performance change relative to the MPS as the trade-off parameter increases?

3. Does one heuristic outperform the others with respect to performance against the MPS and solution quality at all levels of the trade-off parameter?

**Research hypotheses**

**H1.** When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in percent over optimal solution due to a change in the tradeoff parameter.

**H2.** When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in the percent improvement in changeover time against the MPS due to a change in the tradeoff parameter.

**H3.** When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in the percent improvement in lateness against the MPS due to a change in the tradeoff parameter.
4.1.2 The affect of heuristics on changeover time and lateness

The research questions and hypotheses which follow are formulated to provide insight into the performance of the three solution procedures. Since managers will weigh the importance of each objective (i.e. changeover time and lateness), the objective of this comparison is to determine which heuristic operates best under different operating conditions.

Applying a scheduling heuristic to improve one criteria improves the schedule with respect to that particular criteria. The degree of improvement may vary depending on the type of heuristic applied. But what happens to the secondary criteria? Does the performance of the secondary criteria improve also? These following questions are the focus of this dissertation.

5. Does applying a scheduling heuristic to the Master Production Schedule improve the changeover time and lateness performance?

6. Is there a significant difference between heuristics against all performance measurements under different operating conditions?

Research hypotheses

H4. In a manufacturing environment characterized by a given set of operating conditions, there is no significant difference between all three heuristics when measured against all performance measurements?
4.1.3 The affect of problem size

Prior research on production scheduling has indicated that problem size is a key factor influencing the performance of heuristics. There has been conflicting results reported in the literature. Specifically, Gavett (1965) has shown that (a) as problems get larger solution quality improves and Guinet (1993) has shown that as problems get larger solution quality degrades. The natural research question arising in the context of this dissertation are:

7. Does solution quality improve as problem size increases?

8. Does percent improvement in changeover and percent improvement in lateness improve against the MPS as problem size increases?

Research hypotheses

\textbf{H5.} When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in solution quality due to a change in problem size.

\textbf{H6.} When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions there is no significant difference in percent improvement in changeover time and percent improvement in lateness against the MPS due to a change in problem size.

\textbf{H7.} In a manufacturing environment characterized by a given set of operating conditions, there is no significant difference between all three heuristics due to a change in problem size when measured against all performance measurements.
4.1.4 The affect of coefficient of variation of changeover matrix

Prior research on production scheduling with sequence dependent changeovers has indicated that the coefficient of variation of changeover times is a key factor influencing the performance of heuristics. Gavett (1965) in his experiments demonstrated that as the variance of the changeover matrix increased the performance of heuristics decreased relative to the lower bound. This was tested in a single objective sequence dependent changeover time environment. This conclusion by Gavett (1965) leads to an interesting question for the research problem in this dissertation.

9. In a bi-criteria MPS sequence dependent scheduling problem, does solution quality improve as the coefficient of variation changes?

10. In a bi-criteria MPS sequence dependent scheduling problem, does percent improvement in changeover time and percent improvement in lateness improve as the coefficient of variation changes?

Research hypotheses

$H8$. When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in solution quality due to a change in the coefficient of variation of changeover times.

$H9$. When using the same scheduling heuristic in a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in the percent improvement in changeover time and percent
improvement in lateness against the MPS due to a change in the coefficient of variation of changeover times.

**H10.** In a manufacturing environment characterized by a given set of operating conditions, there is no significant difference in all performance measures between heuristics due to a change in the coefficient of variation of changeover times.

### 4.2 Rationale for choosing the experimental design

There are several reasons for choosing the experimental design used in this study. First, no analytical procedure is known to exists for obtaining an optimal solution for the size of problems we are studying (e.g. problems in excess of 100 orders). Second, the study of several operating factors increases the complexity of the problem and can best be analyzed under the proposed design. Thus, in view of the computational complexity involved and the exploratory nature of this study an experimental research methodology is adopted. Finally, since the objective of this study is (a) to identify the nature and form of the relationship between changeover time and lateness and (b) to compare the performance of three different scheduling heuristics under changing operating conditions an experimental approach seems most appropriate.

### 4.3 Experimental variables

A production manager who wants to schedule a processor using two criteria, (changeover time and lateness) face the choice of one of the procedures outlined in chapter 3. We believe that this choice will depend on the particular settings of the experimental variables which effect relative performance of the scheduling procedures. In this section we will discuss two groups of experimental variables. These include three
dependent variables involving: (1) percent improvement in changeover time against the initial MPS; (2) percent improvement in lateness against the initial MPS; (3) percent of the optimal solution; and four independent variables involving: (1) coefficient of variation of changeover matrix; (2) problem size, (3) tradeoff parameter; (4) scheduling heuristics.

4.4 Performance measurements

The research problem, re-sequencing the MPS to minimize changeover time and lateness is solved using each of the three solution procedure; the simulated annealing heuristic, 3-OPT heuristic, and the Construction heuristic. The performance measurements gathered in this process are the changeover time and lateness measurements. In this research, performance is measured in terms of improvement against the initial MPS and solution quality (performance measured against the optimal solution). Complete enumeration will be used for smaller problems (i.e. problems with 10 orders) to determine the optimal solution. In this dissertation the optimal solution is the minimum value of the linear combination of changeover time and lateness. The solution quality of each of the heuristics is measured by expressing the difference between heuristic and optimal solution as a percentage of the optimal solution. This transformation of the data was performed according to equation (4.1).

\[
\text{Solution Quality} = \frac{\text{Heuristic Solution} - \text{Optimal Solution}}{\text{Optimal Solution}} \times 100
\]  

(4.1)
To test the performance of the heuristic procedures against the MPS we will measure the percentage improvement in changeover time and the percent improvement in lateness from the initial MPS schedule. The MPS provides an initial solution in which we attempt to improve by applying heuristic procedures. This transformation of the data was performed according to equation (4.2).

\[
\text{Improvement} = \frac{\text{MPS Solution} - \text{Heuristic Solution}}{\text{MPS Solution}} \times 100
\]  

(4.2)

4.5 Operating and decision variables

The research hypotheses outlined later in this chapter are evaluated by conducting simulation experiments. In developing the computer simulation model, several operating variables were considered for inclusion in the model. Some of the variables considered are included in the model as fixed factors throughout all of the computer runs made with the program. The fixed factors (including the beginning inventory levels, the processing run time, the lead time, and the lot sizing rule) are assigned fixed values\(^1\) because: (1) their effect upon the relative operating performance of the scheduling procedures is believed to be negligible; and, or, (2) the size of the experiments would have grown prohibitively large had they been allowed to vary.

Other independent variables, upon which this study is focused, are believed to have a major effect upon the relative performance of the scheduling procedures. These include,
operating variables (coefficient of variation of changeover matrix, and problem size), and
decision variables (trade-off parameter and scheduling heuristics). These variables are
included in the model and the values assigned to them are changed during the computer
runs in order to study the scheduling heuristics under a variety of operating conditions.
Analysis of previous research provide the input for choosing appropriate factor level
settings for an experimental design to test the proposed scheduling heuristics (see Table
1).

4.5.1 Coefficient of variation (CV)

The coefficient of variation of a changeover matrix is a very important factor in
chemical processing companies. In these industries product changeover times are
sequence dependent which effects how these firms plan and control their operations.
Previous research by Gavett (1965) has shown that increases in the coefficient of variation
of changeover times reduce the solution quality of scheduling heuristics. This research is
designed to provide further insight into the important effect of coefficient of variation of
changeover time. This factor has not been studied in previous Master Production
Scheduling research under the criteria considered in this dissertation. Thus considering
product changeovers and the coefficient of variation of the changeover matrix in our
experimental design contributes to the MPS literature.

The coefficient of variation used in this dissertation is based on a changeover
matrix obtained from a chemical processing firm. Using this matrix two similar matrices

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1 The fixed values of the control variables are set at levels found either in sequence dependent scheduling
literature and in actual chemical processing firms.
were generated which have the same mean but different variances. The two levels of coefficient of variation in this study are:

\[(a) \ CV = .3, \ (b) \ CV = 1.2.\]

These levels are representative of what we have seen in real operating environments. They are also an extension of the sequence dependent changeover time literature in that a coefficient of variations beyond .87 has not been examined.

### 4.5.2 Problem size / Time between orders (TBO)

The number of orders in the MPS is expected to have an important effect on the efficacy of the heuristics. Berry et.al (1999) has shown this factor to be of significance when performance is compared against the initial MPS relative to changeover time reduction. Other authors have noticed that solution quality is not affected by problem size though the problem becomes more difficult to solve. In order to investigate how these heuristics performed relative to problem size for a bi-criteria MPS problem with sequence dependent changeovers, problem size is set at \( n = 10 \) and \( n = 100 \) orders. These order sizes are consistent to what practicing managers experience, and contributes to the literature by examining performance under larger problems. To control for the number of orders in the MPS we will adjust the time between orders (TBO). A small TBO corresponds to frequent orders (large problem size) and a high TBO corresponds to infrequent orders (small problem size).
4.5.3 Tradeoff parameter ($\omega$)

In the formulation of the objective function (see chapter 3), $\omega$ was used to determine the tradeoff between the two objective functions, changeover time and lateness. If $\omega = .999$, the formulation represents the single objective of minimizing changeover times, and if $\omega = 0$, it represents the single objective of minimizing lateness. If $0 < \omega < 1$, the objective to be considered is a weighted sum of changeover times and lateness. In order to test the significance of this factor, the tradeoff parameter will be investigated at three levels:

(a) $\omega = 0.001$ (single objective minimizing lateness)
(b) $\omega = 0.5$ (bi-criteria: minimizing weighted sum of changeover times and lateness)
(c) $\omega = .999$ (single objective minimizing changeover times)

4.5.4 Heuristics

In chapter three we discussed in detail three solution procedures for solving the bi-criteria Master Production scheduling problem with sequence dependent changeovers. Thus, to avoid repetition, no further elaboration on these procedures is presented here.

4.6 Experimental design

The main purpose of the experiments is to compare the relative performance of the three heuristic methods under different tradeoff parameters at selected factor level
combinations (see Table 2). The details of the experimental design, the experimental procedure, and the analysis performed are presented in the following sections.

A completely randomized four-way full factorial design is used to provide insight into the research questions. The independent variables included in this design can be classified into decision variables and operating factors which concern the product and process characteristics. There are two decision variables: the heuristic procedure, and the tradeoff parameter. The two operating factors included in the experiments are problem size, and coefficient of variation of changeover times.

4.7 Experimental procedure

The simulation model is written in Fortran with separate programs for each of the heuristic methods. Source listings of the computer programs are presented in Appendix A. This program is used to generate the experimental data to identify the important relationships and to answer the research questions above. The following procedures are used in the data collection.

4.7.1 Four-Way ANOVA design

1. There are four combinations of coefficient of variation of changeover times and problem size.

2. As a function of problem size, the trade-off parameter is considered at three levels. Combined with the four operating conditions, these generate twelve experimental combinations.
3. These 12 combinations provide 36 experimental settings when combined with the three scheduling procedures. Performance data is captured for each of the 12 settings for each heuristic.

4. Ten replications are performed for each factor level combination giving a total of 360 replications.

4.7.2 Methods of analyses performed

The stated objectives of this experimental comparison are to determine the relative advantage of one scheduling procedure over another in terms of solution quality and improvement in the Master Production Schedule, and to determine whether the operating conditions affect the results obtained. The identification of the methods of analyses used to determine the statistical significance of these relationships is an important part of the experimental design. The experimental results will be analyzed in three stages. First, a t-test will be used to test the significance of the scheduling heuristics against the initial MPS. Second the Analysis of Variance procedure will be employed to analyze the performance measurements and to identify the main effects. Third, the data is graphically analyzed to understand the important relationships between the product characteristics and decision variables.

4.7.3 T-test

The performance difference between the initial MPS and the scheduling heuristics are analyzed using the data gathered from the simulation experiments. To test the null
hypotheses that there is no significant difference in performance between the initial MPS and the three scheduling heuristics the t-test will be used.

4.7.4 ANOVA analysis

The performance difference between the three scheduling heuristics are analyzed using the data gathered from the simulation experiments. These analyses are used to identify the significant main effects of the decision variables and operating conditions, and their two-factor interaction effects. Higher order interactions, such as three-factor interactions are not estimated. The ANOVA results are augmented by conducting multiple comparisons using Tukey’s pairwise comparison procedures where appropriate.

4.7.5 Graphical analysis

A graphical analysis helps in identifying the nature of relationships between our performance measurements and the experimental factors. Separate graphs of the performance measurements and each of the two operating variables (i.e. coefficient of variation of changeover times and TBO), are drawn for all three scheduling procedures at all levels of the tradeoff parameter. These plots provide insights into the nature of the relationships between scheduling procedures and operating factors.

4.8 Computer simulation model

The computer simulation model is used to test the hypotheses formulated in the previous section. The simulation program models a single stage bi-criteria Master
Production Schedule in a make to stock process industry operation with sequence dependent changeovers. The subjects in this dissertation includes ten different products, each having the following data: average period sales forecast, the economic MPS batch size, the MPS initial inventory, the processing time (in units/hr which is constant for all products), and the changeover time matrix. The remainder of this section includes a more detailed description of several features of the model.

4.8.1 Subject generation

The initial subject reflects actual operating data obtained in field research from a chemical processing firm. For the remaining nine subjects, the following procedure was used to randomly generate the product structure data for each of the ten products. First, an average period demand was randomly generated from a uniform distribution with a mean of 170,085, a lower limit of 3846 and an upper limit of 336,323. Second, given the economic time between MPS orders (TBO) the batch size was computed to be the average period demand multiplied by the time between orders (TBO) value. The lead time was fixed at zero, and the beginning inventory value was set at a fraction of the weekly demand with range between (.2 and .8). The lot sizing rule chosen was fixed order quantity. In these experiments the demand forecast and the initial inventory conditions were identical across the entire planning horizon for all ten subjects, therefore the difference in performance between the subjects resulted from differences in the randomly generated average period forecast and TBO values.
4.8.2 Starting conditions

An MPS record was established for each product, which contained forecast, projected inventory, and MPS rows. These records were processed to develop a 60 period MPS for each product. To eliminate the effect of transient conditions upon the operating performance measures the first 60 periods of operating performance data in each simulation run are discarded. The 60 period initialization interval was selected after visual inspection of the inventory levels.

4.9 Summary

This chapter described the research design used in this dissertation. First, we discussed the research questions and presented the formal research hypotheses. We then discussed the reasons for choosing a simulation experiment approach. This was followed by the experimental variables and the experimental design. It was followed by a description of the analysis for testing the hypotheses and the simulation. The next chapter presents the experimental results and the final chapter outlines the major contributions and suggestions for future research.
Decision Variables

1. Trade-off Parameter (\(\omega\))
   Levels: .001, 0.5, .999

2. Heuristic Procedures
   Levels: Simulated Annealing, 3-OPT, Construction Heuristic

Operating Variables

1. Coefficient of Variation (CV)
   Levels: 0.3, 1.2

2. Problem Size
   Levels: 10, 100

Table 4.1 Factors and levels for experimental design

<table>
<thead>
<tr>
<th>3-OPT</th>
<th>SA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\omega_1) (\omega_2) (\omega_3)</td>
<td>(\omega_1) (\omega_2) (\omega_3)</td>
</tr>
</tbody>
</table>

- CV (low)
- Problem Size (small)
- CV (high)

- CV (low)
- Problem Size (large)
- CV (high)

Table 4.2 Experimental design

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CHAPTER 5

EXPERIMENTAL RESULTS

This chapter presents the results of the computer simulation experiments that were described in Chapter 4 and provides detailed analysis of those results. The chapter begins with a presentation of the results and data analysis of the experiments concerned with applying Master Production scheduling heuristics to the initial MPS. These results will be presented in accordance with the research hypotheses presented in Chapter 4.

Recall that three general issues regarding Master Production scheduling procedures are addressed by this research; (1) the effect of operating conditions upon the relative performance of the three heuristics; (2) the relative operating performance of the scheduling heuristics in improving the initial MPS performance (changeover time and lateness); and (3) the relative operating performance of the scheduling heuristics versus the optimum solution.

Before we can address these points above, the data was statistically analyzed to test the reasonableness of the data and to check the degree of conformance of the data to the assumptions of the ANOVA model which was used for testing the statistical hypotheses. We first present data that tests the reasonableness of our results. These tests are presented in two forms. First, a T-test is used to test the null hypotheses that there is
no significant difference in performance between the initial MPS and the scheduling heuristics. Second, a One Way ANOVA is used to test the hypotheses that there is a significant difference in performance between the three levels of the tradeoff parameter.

After the reasonableness tests are presented, we use ANOVA to test the three general issues mentioned above. Under each level of the tradeoff parameter the following will be discussed: (1) the effect of the coefficient of variation and problem size on performance (2) the relative operating performance of the scheduling heuristics (3) tradeoffs that occur between changeover time and lateness. Finally the results of the scheduling heuristics against the optimal solution for small problem sizes will be presented.

One series of experiments under twelve different sets of operating conditions was performed in order to study the research hypotheses. In this chapter, the results of the experiments are presented and analyzed separately in regard to each of the issues identified above. Each of the twelve operating environments (OEN) are presented in Table 5.1 for each scheduling heuristic.

The following statistical results are outlined in a way that support the research hypotheses that were outlined in chapter 4. The reasonableness tests support the null hypotheses that there is no significant difference in percent improvement in changeover time and lateness against the initial MPS at all levels of the tradeoff parameter. After the reasonableness test has been conducted the next set of results support the null hypotheses that there is no significant difference in percent improvement in changeover time and lateness against the initial MPS at both levels of problem size and the coefficient of variation of changeover times. The third set of results supports the null hypotheses that there is no
significant difference in scheduling heuristics at all levels of problem size and coefficient of variation of changeover times. We examine these null hypotheses at all levels of the tradeoff parameter.

5.1 Operating performance of initial MPS vs. scheduling heuristics

The results of applying the T-test to the initial MPS and the scheduling heuristics data are presented in Table 5.2 for total changeover time. The results indicate that in certain operating environments there is a significant difference in changeover time between the initial MPS and the scheduling heuristic. The shaded areas indicate a significant improvement in changeover time. For example, the results indicate that there was a significant difference between 3-OPT and the initial MPS (at the .05 level) under small problems with low coefficient of variation of changeover times and 99% of weight placed on reducing changeover time. The corresponding t-value indicates the direction of the change in changeover time. Thus in this environment we reject the hypotheses that there was no significant improvement in changeover time between the initial MPS and the scheduling heuristic. In this cases one would expect that changeover time would be reduced under conditions where 99% of the weight is placed on changeover time. A detailed inspection of the data revealed that scheduling heuristics improve changeover time across a broad range of operating conditions. The effect of operating conditions and scheduling heuristics will be further analyzed in a later section.

A detailed analyses of the lateness data is shown in Table 5.3. The lateness data was analyzed in a similar fashion (i.e., a t-test was performed to determine whether there was a significant difference in lateness between the initial MPS and scheduling heuristic).
The results for 3-OPT and SA indicate that under certain operating conditions there is a significant improvement in lateness against the initial MPS. For example, when 99% of weight is placed on reducing lateness there is a significant improvement in lateness against the initial MPS under all operating environments. Thus in these environments the hypotheses that there was no significant improvement in lateness between the initial MPS and the scheduling heuristic was rejected. A detailed inspection of the data revealed that scheduling heuristics improve lateness across a broad range of operating conditions.

The overall conclusion of the effect of the scheduling heuristics against the initial MPS was that the results were encouraging in that scheduling heuristics improve performance across a broad range of operating conditions and that, consequently, a more detailed investigation of those results could provide meaningful conclusions regarding the effect of operating conditions on performance and the relative operating performance of the three scheduling heuristics.

The summary suggests some important insights into the operating performance of the three scheduling heuristics:

1. The operating performance of the scheduling heuristics is superior to that of the initial MPS across a broad range of operating conditions for all three heuristics.

2. The Construction heuristic is more robust at reducing changeover time (6 of the 12 operating environments) than it is at decreasing total lateness (0 of the 12 operating environments).

3. The 3-OPT Heuristic and SA is effective at reducing changeover time (9 of the 12 operating environments) and at decreasing total lateness (7 of the 12 operating environments).
The general conclusion that can be drawn from the various analyses presented in this section is that the performance of the scheduling heuristics is superior to the initial MPS with respect to both criteria across a broad range of operating conditions. Thus, strictly from a performance standpoint, the scheduling heuristics is preferred to the initial MPS in a majority of OEN’s. More analysis will be done on the effect of operating conditions on performance in a later section.

Thus far, this discussion of the effect of scheduling heuristics upon the relative performance of the initial MPS has focused on total changeover time and total lateness time as performance measurements. Though some interesting conclusions were drawn from that analysis, some additional insights can be drawn by also considering the relative magnitude of the performance advantage enjoyed by the heuristic procedures across the twelve operating environments. Thus, Table 5.4 presents data on the percentage improvement in changeover time and percentage improvement in lateness time when moving from the initial MPS to the final MPS. The percent improvement was calculated only in those cases where there was a statistically significant difference in the performance of the initial MPS and the scheduling heuristics. It is evident from Table 5.4 that under certain operating conditions performance improves 70% - 80% over the initial MPS. Such large performance improvements will be investigated in later sections.

The results in Table 5.4 indicate that the weight placed on the two criteria (tradeoff parameter), the value of the coefficient of variation of the changeover matrix, and the number of orders in the MPS (problem size) have impact upon the relative magnitude of the performance advantage enjoyed by using the scheduling heuristics. In
order to more clearly understand the underlying causes of these results, a number of 
follow-up analyses were performed. The following section addresses the effect of the 
decision variable (tradeoff parameter) on the percentage improvement in changeover time 
and lateness time.

5.2 The effect of tradeoff parameter on performance

To further understand the effect of the tradeoff parameter a ONE WAY ANOVA 
design was used to determine the effect of the tradeoff parameter (ω) on percentage 
 improvement in changeover time and percentage improvement in lateness. This design was 
averaged across all heuristics, problem sizes and coefficient of variation of changeover 
matrices (CV). The results are shown in Tables 5.5 and 5.7 for percent improvement in 
changeover time and percent improvement in lateness respectively. Table 5.5 indicates that 
the main effect of tradeoff parameter is significant at (p = .05). The Tukey analysis (Table 
5.6) shows there is a significant difference in percent improvement in changeover between 
all levels of the tradeoff parameter. Table 5.7 indicates that the main effect of the tradeoff 
parameter is significant (at the .05 level) for percent improvement in lateness. The Tukey 
analysis (Table 5.8) shows the difference in performance is between levels $W_{\text{clo}}$ and $W_{\text{equal}}$ 
and levels $W_{\text{clo}}$ and $W_{\text{late}}$ but not between levels $W_{\text{equal}}$ and $W_{\text{late}}$. This is an interesting 
result because the marginal improvement between placing equal weight on both criteria 
and 99% of weight on lateness is not statistically significant. Figures 5.1 and 5.2 show the 
effect of the tradeoff parameter on percent improvement in changeover time and percent
improvement in lateness respectively. In light of the analysis presented in Tables 5.6 and 5.8 along with Figures 5.1 and 5.2 the following are general observations:

1. A larger percentage improvement in changeover time is obtained when the majority of the weight is placed on reducing changeover time than when weights are split equally between the two criteria or the majority of weight is on reducing lateness.

2. There is no significant difference in percent improvement in lateness time when the majority of the weight is placed on reducing lateness or when the weights are split equally between the two criteria. Though there is significant improvement in performance when the majority of weight is placed on reducing lateness versus when a majority of weight is placed on reducing changeover time.

The general conclusions drawn from this analysis is that the percent improvement in changeover time and lateness time is dependent on the emphasis a decision maker places on the two criteria. However, there is no significant difference in lateness between equal weights placed on both criteria and a majority of the weight placed on lateness. This is partly due to the initial MPS already being in EDD order which minimizes tardiness.

Though the proceeding analysis on the tradeoff parameter helped to explain the improved performance, it provided no insight as to the effect of problem size and coefficient of variation on performance and the relative performance between the three heuristics. The next section explores the effect of these operating conditions on performance. Building on what we already know about the effect of the tradeoff.

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1 $W_{oc}$ indicates that the decision maker places the majority of the weight on reducing changeover time. $W_{eq}$ indicates the weight is distributed equally between changeover time and lateness. $W_{late}$ indicates
parameter, the operating conditions will be explored at each level of the tradeoff parameter.

5.3 The main effect of operating conditions at tradeoff parameter = changeover

In this section we analyze the effect of problem size, CV and heuristics when a decision maker places 99% of weight on reducing changeover time. To test the effect of operating conditions, a completely randomized full factorial ANOVA design was used to determine the effect of (i) Scheduling Heuristics (ii) Coefficient of Variation of the changeover matrix and (iii) problem size on both performance measurements. The results can be seen in Table 5.9. This design is averaged across all heuristics, problems sizes and CV’s. The Tukey pairwise comparison test (Table 5.10) is used to determine the significance between the three different scheduling heuristics.

5.3.1 Main effect of problem size and CV

The ANOVA results (Table 5.9) indicate that problem size and CV are significant at \( p = .05 \) for percent improvement in changeover time. The means are averaged across all heuristics and are shown in Table 5.11. Figures 5.3 and 5.4 represent the main effect of problem size and CV graphically. It is apparent that as problem size increases the percentage improvement in changeover time increases. This increase ranges from 35 percent to 75 percent. The same result holds true for the coefficient of variation of the changeover matrix, as CV increases there is a significant improvement in changeover time.

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the majority of the weight is on reducing lateness.

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from the initial MPS. This increase ranges from 50 percent to 60 percent. Large problems gives more opportunity for like products to be batch together, thus reducing changeover time. High CV leads to more opportunities for heuristics to reduce changeover time because of the high variance between products. The results in Table 5.9 also indicate there is no significant interaction between problem size and CV (at p = .05). Figure 5.5 shows the relationship between problem size and CV.

5.3.2 Main effect of scheduling heuristics

The ANOVA results in Table 5.9 indicate that the main effect of scheduling heuristics is not significant at (p = .05) for percent improvement in changeover time. The Tukey analysis (see Table 5.10) indicates that there is no significant difference between heuristics in percent improvement in changeover time. The average percent improvement in changeover time was 57.8 percent for 3-OPT, 52.5 percent for SA, and 54.3 percent for Construction. From an earlier discussion we noted that there was no significant improvement in lateness when 99% of weight is on reducing changeover time (see Table 5.3). One important point to make is that under these conditions where a decision maker places 99% of weight on improving changeover time there is a degradation in lateness performance. The next section analyzes the tradeoff that occurs.

5.3.3 Tradeoff

Though there are significant reductions in changeover time observed when the majority of the weight is on changeover time, in three of the four operating environments
there is a significant tradeoff (OEN’s 1, 7, and 10) between changeover time and lateness in the MPS. (See Table 5.1 for a Table on Operating Environments)

A graphical analysis of a trade-off between changeover time and lateness time can be seen in Figure 5.6. OEN 1 resembles an environment where problem size is low and CV is low. The results indicate that a reduction in changeover time leads to an increase in lateness. This result has important implications for the practicing production manager. The implication here is that it may not be cost effective to implement heuristics in this operating environment where the majority of the weight is placed on reducing changeover time. The 40 to 60 percent improvement in changeover must be weighed against the significant increase in lateness.

Though the main effect of scheduling heuristics was shown to be statistically significant, the results in Table 5.11 were inspected further in a later section in an attempt to identify in what operating environments are individual heuristics more effective in reducing changeover time. The information in this section provides useful insights regarding the effect of operating conditions on performance when the decision maker places the majority of emphasis on reducing changeover time. The following are general conclusions generated from the analysis above.

1. When the majority of the weight is placed on changeover time there is no significant difference between scheduling heuristics on percent improvement in changeover time.

2. When the majority of the weight is placed on changeover time the percent improvement in changeover time increases as problem size increases.
3. When the majority of the weight is placed on changeover time, the percent improvement in changeover time increases as the coefficient of variation of the changeover matrix increases.

4. In Operating Environments 1, 7, and 10 there is a significant tradeoff between percent improvement in changeover time and percent increase in lateness time.

5. The scheduling heuristics are most effective in reducing changeover time in an operating environment characterized by large problem size and a high coefficient of variation.

6. When the majority of the weight is placed on changeover time there is no significant improvement in lateness. In fact there is a significant degradation in lateness against the initial MPS. Once again, these results indicate that reasoning should be exercised in making the decision to implement scheduling heuristics since operating conditions do have an effect upon the benefits that they can provide. Specifically, under certain operating conditions (large problems), the improvement in changeover time provided by the scheduling heuristic may be achieved at the expense of degradation in lateness. Consequently, the production manager is advised to conduct a pilot study to estimate where there plant is relative to the parameters outlined in this study.

5.4. Main effect of problem size and CV at tradeoff parameter = equal

The ANOVA results (Tables 5.12 and 5.14) indicate that problem size and CV are significant at (p = .05) for percent improvement in changeover time and percent improvement in lateness. Tables 5.16 and 5.17 are the means averaged across all heuristics for percent improvement in changeover time and percent improvement in lateness.
respectively. Figures 5.7 and 5.8 represent the main effect of CV averaged across all heuristics for percent improvement in changeover time and percent improvement in lateness respectively. It is apparent that as CV increases the percentage improvement in changeover time and the percentage improvement in lateness increase. The percent improvement in changeover time increases from .85% to 27.5% and the percent improvement in lateness increases from 19% to 45.9%. This is because as the variance in a changeover matrix increases more opportunities exists for heuristics to improve both changeover time and lateness. Though for problem size this relationship does not hold true. Figures 5.9 and 5.10 represent the main effect of problem size averaged across all heuristics for percent improvement in changeover time and percent improvement in lateness respectively. Percent improvement in changeover time decreases from 22.1% to 8.3% as problem size increases and percent improvement in lateness increases from 24.2% to 40.1%. Changeover time decreases under large problems because heuristics are less likely to batch similar products together due to increased pressure on lateness performance. Percent improvement in lateness increases as size increases because under small problems the MPS is relatively efficient with respect to the total number of lateness hours. Larger problems lead to more opportunities for performance improvement.

The results also indicate there is a significant interaction between problem size and CV (at $p = .05$) for percent improvement in changeover time but the interaction is not significant (at $p = .05$) for percent improvement in lateness time (See Figures 5.11 and 5.12). The effect of CV on percent improvement in changeover time is not the same for small problems sizes as it is for large problem sizes. As CV increases the rate of
improvement in changeover time is larger for smaller problems than for larger problems. For percent improvement in lateness the effect of CV on performance is the same for small problems as it is for large problems. The results in Table 5.16 indicate that the largest improvement in changeover time occurs in small problems with high CV’s and the smallest occurs in large problems with a low CV. Likewise, for percent improvement in lateness, the results show that the largest improvement in lateness occurs in large problems with high CV’s and the smallest improvement occurs in small problems with small CV’s (See Table 5.17).

5.4.1 Main effect of scheduling heuristics

An ANOVA design was used to test the main effect of scheduling heuristics when equal weights are placed on both criteria. The results indicate the main effect of heuristics is significant (p=.05) for both percent improvement in changeover time and percent improvement in lateness. The results are shown in Tables 5.12 and 5.14a. The Tukey pairwise means tests (Tables 5.13 and 5.15) shows that there is no significant difference in either performance measurement between 3-OPT and SA but there is a significant difference in performance between 3-OPT and Construction and between SA and Construction. This difference in performance between the Construction heuristic and the other two is due to the inability of the Construction heuristic to improve lateness performance. SA and 3-OPT are more robust insertion heuristics designed to handle multiple criteria.
5.4.2 Tradeoff

Some very interesting results occur when equal weights are placed on both criteria. The tradeoffs that exist when 99% of weight is placed on changeover time are not as apparent under equal weights. In fact under certain operating conditions simultaneous improvement in both criteria exists. For example in OEN 5 which is characterized by small problems and high CV there is an improvement in both changeover time and lateness time. Figure 5.13 shows the improvement in both changeover time and lateness time when equal weights are placed on both criteria. Now if we examine OEN 8 which is characterized by large problem size and low CV there exists a tradeoff between changeover time and lateness time. Figure 5.14 shows the tradeoff between changeover time and lateness time when equal weights are placed on both criteria. It is evident from these results that under high CV improvement in both criteria can be obtained using scheduling heuristics while under low CV tradeoffs between changeover time and lateness must be considered.

Once again, these results indicate that care should be exercised in making the decision to alter the initial MPS with scheduling heuristics since operating conditions do have an effect on performance measurements. The information in this section provides useful insights regarding the effect of operating conditions upon the performance of the MPS when equal weights are placed on both criteria. The following are general conclusions generated from the analysis above.

1. When equal weight is placed on changeover time and lateness there is no significant difference in percent improvement in changeover time between 3-OPT and SA, but there is a significant difference between 3-OPT and Construction and between SA and Construction.
2. When equal weight is placed on changeover time and lateness time the percent improvement in changeover time decreases as problem size increases.

3. When equal weight is place on changeover time and lateness time the percent improvement in lateness time increases as problem size increases.

4. When equal weight is placed on changeover time and lateness time the percent improvement in changeover time and the percent improvement in lateness time increases as the coefficient of variation of changeover matrix increases.

5. Statistically, the scheduling heuristics perform the best with regards to changeover time in an environment where there is a small number of orders and a large CV.

6. Statistically, the scheduling heuristics perform the best with regards to lateness in an environment where there is a large number of orders and a large CV.

5.5 Main effect of problem size and CV at tradeoff parameter \( \Rightarrow \) lateness

The ANOVA results in Tables 5.18 and 5.20 indicate that the main effect of coefficient of variation of the changeover matrix and problem size are significant at (\( p =.05 \)) for both percent improvement in changeover time and percent improvement in lateness. Tables 5.22 and 5.23 are the means averaged across all heuristics for percent improvement in changeover time and percent improvement in lateness respectively.

Figures 5.15 and 5.16 show the main effect of problem size on both performance measurements, while Figures 5.17 and 5.18 show the main effect of CV.

The results for percent improvement in changeover time indicates that as problem size increases the percent improvement in changeover time decreases and as CV increases
the percent improvement in changeover time increases. This result indicates that even though 99% of weight is on reducing lateness improvement in changeover time still occurs. The results also indicate that as problem size increases the percent improvement in lateness time increases and as CV increases the percent improvement in lateness increases. Thus as expected significant improvement in lateness occurs when 99% of weight is placed on lateness.

The interaction between problem size and the coefficient of variation is significant at (p=.05) for percent improvement in changeover time and percent improvement in lateness (See Tables 5.18 and 5.20). These results are shown in Figures 5.19 and 5.20. The results indicate that the effect of CV on performance (changeover time and lateness) is not the same for small problems as it is for large problems. Under low CV the percent improvement in changeover time is not significantly different from the initial MPS for small or large problems. Though as we increase CV the percent improvement in changeover time increases at a faster rate for smaller problems than large problems. This is because for small problems with low CV there is not much improvement against the initial MPS because of the small number of orders and the low variance in the changeover matrix. Whereas for large problems with low CV there is more opportunity to improve the initial schedule because of the large number of orders. Thus we see a more significant increase in performance as we move from low CV to high CV under smaller problems than larger problems.
5.5.1 Main effect of scheduling heuristics

A full factorial ANOVA design was used to test performance when 99% of weight is on reducing lateness. The results indicate that there is a significant difference (p=.05) due to a change in heuristics for both percent improvement in changeover time and percent improvement in lateness. Again, these results are averaged across all problem sizes and coefficients of variations. The results are shown in Tables 5.18 and 5.20 for percent improvement in changeover time and percent improvement in lateness respectively. The Tukey pairwise means test (Table 5.19 and 5.21) indicates that 3-OPT and SA outperform the Construction Heuristic for both performance measurements and that there is no significant difference between 3-OPT and SA. Again the Construction heuristic is not designed to minimize lateness subject to plant restrictions like sequence dependent changeovers.

5.5.2 Tradeoffs

When a decision maker place 99% of weight on reducing lateness the operating factors outlined in this study have a significant effect on performance. As shown in an earlier section the levels of the operating factors influences the direction of both performance measures. Under operating conditions characterized by high CV (OEN’ 6 and 12) significant improvements in both criteria exists (see Figures 5.21 and 5.22). Versus operating environments characterized by low CV (OEN’s 3 and 9) either tradeoffs occur between both criteria or there is no significant improvement against the initial MPS.
This result has important implications for the production manager. Unlike when a majority of the weight is placed on reducing changeover time, under certain operating conditions managers can expect tradeoffs between changeover time and lateness or simultaneous improvement between the two performance measures. The following are general observations from this section:

1. When the majority of weight is placed on lateness there is a significant difference between 3-OPT and Construction and between SA and Construction on percent improvement in changeover time and percent improvement in lateness, while there is no significant difference between 3-OPT and SA.

2. When the majority of weight is placed on lateness the percent improvement in changeover time increases as CV increases using 3-OPT or SA.

3. When the majority of weight is placed on lateness the percent improvement in lateness increases as CV increases using 3-OPT or SA.

4. When the majority of weight is placed on lateness the percent improvement in changeover time decreases as problem size increases using all three heuristics.

5. When the majority of weight is placed on lateness the percent improvement in lateness increases as problem size increases using 3-OPT or SA.

6. When the majority of weight is placed on lateness OEN's operating environments characterized by high CV provide significant improvement in both criteria using 3-OPT or SA.

Thus, it appears that the improved operating performance of the final MPS relative to that of the initial MPS can be traced to significant changes in the coefficient of variation of the changeover matrix and problem size.
Though the proceeding analysis helped to explain the effect of problem size and CV on performance, it provided no insight as to the relative performance of scheduling heuristics within each problem environment. These four problem environments were shown in Table 5.11. The following section examines the relative performance of scheduling heuristics within each operating environment. This section also includes interaction effects between: (1) heuristics and problem size; and (2) heuristics and CV.

5.6 The effect of operating conditions on the performance of scheduling heuristics. Tradeoff parameter = changeover

A two-way ANOVA design was used to test the interaction of CV and problem size with heuristics. The tradeoff parameter is fixed at a certain level and either the CV or problem size is fixed at a certain level. This test was run under every combination of problem size and coefficient of variation of the changeover matrix. Thus there are four combinations of problem size and CV (see Table 5.11). The Tukey pairwise means test will be used to determine the level of significance between the scheduling heuristics. Each section that follows will further explore these interactions.

5.6.1 The interaction of CV and heuristics at small problem sizes.

In this section we will analyze the effect of CV and heuristics on performance under small problem size conditions. The results of the two-way ANOVA can be seen in Table 5.24. for percent improvement in changeover time. The main effects of scheduling heuristics and CV are significant at \( p = .05 \) for percent improvement in changeover time.

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The results indicate that in an environment characterized by small problem size there is a significant difference in percent improvement in changeover between heuristics.

The interaction between CV and heuristics is also significant at (p = .05). The results are presented in Figure 5.23. Looking at the graph in Figure 5.23 it is apparent that as CV increases performance increases for 3-OPT and Simulated Annealing but the Construction heuristic performance holds constant. Thus CV has no effect on the Construction heuristic under small problem sizes. The Tukey pairwise comparison results in Tables 5.25 and 5.26, indicates that there is no significant difference between heuristics at low CV, though a significant difference between both 3-opt and SA with Construction under high CV. From this analysis the following are general observations.

1. In a manufacturing environment characterized by small problem size and w = changeover, there is a significant interaction at p = .05 between heuristics and CV for percent improvement in changeover time. The results indicate that there is no significant difference between heuristics at a low CV though a significant difference between both 3-OPT and SA with Construction at a high CV. Performance increases for 3-OPT and SA as CV increases but for the Construction heuristic performance holds constant.

2. When measuring the percent improvement in lateness performance is significantly worse than the initial MPS at small CV and at high CV.

5.6.2 The interaction of CV and heuristics at large problem sizes.

Results from the two-way ANOVA experiment can be seen in Table 5.27 and Figure 5.24. The ANOVA results indicate that the main effect of CV and heuristic is significant at p = .05. The interaction between heuristics and CV is also significant at p =
.05. It is apparent from Figure 5.24 that the Construction heuristic has a larger percent improvement in changeover time than both 3-OPT and SA for both levels of CV. The Tukey pairwise results (see Tables 5.28b and 5.29) indicate there is a significant difference between heuristics at both low CV and high CV. Again as the CV increases the Construction heuristic's performance holds constant while 3-OPT and SA performance increases slightly. The Construction heuristic outperforms 3-opt and SA under large problems because there are more opportunities to produce similar orders. From these results the following are general conclusions.

1. In a manufacturing environment characterized by large problem size and \( w = \text{changeover} \), there is a significant interaction at \( p = .05 \) between heuristic and CV for percent improvement in changeover time. The results indicate that the Construction heuristic has a larger percentage improvement in changeover time under low CV and high CV than both 3-OPT and SA.

2. When measuring the percent improvement in lateness performance is significantly worse than the initial MPS at small CV and at high CV.

5.6.3 The interaction of problem size and heuristics at low coefficient of variation.

The results of the two-way ANOVA are shown in Table 5.30 and Figure 5.25. The interaction between problem size and heuristic is significant at \( p = .05 \). Thus the effect of problem size on percent improvement in changeover time is not the same for all heuristics. The Tukey pairwise comparison for this combination of problem size and CV has already been examined (See Tables 5.25 and 5.28). Under small problem size there is no
significant difference between heuristics though under large problem size there is a significant difference between heuristics. By looking at Figure 5.25 the Construction heuristic significantly outperforms both 3-OPT and SA, and 3-OPT significantly outperforms SA. Again we see the Construction heuristic outperforms the other two under large problems. The following general conclusions can be made from the statistical results:

1. In a manufacturing environment characterized by low CV and w = changeover, there is a significant interaction at p = .05 between heuristic and size for percent improvement in changeover time. The results indicate that there is no significant difference between heuristics at small problem sizes and a significant difference between heuristics at large problem sizes. Performance increases for all heuristics as problem size increases. The Construction heuristic outperforms 3-opt and SA under large problems and low CV.

2. When measuring the percent improvement in lateness performance is significantly worse than the initial MPS under small problems and large problems.

5.6.4 The interaction of problem size and heuristics at high coefficient of variation.

The results of the two-way ANOVA are shown in Table 5.31 and Figure 5.26. The results indicate the interaction between problem size and heuristics is significant at p = .05 for percent improvement in changeover time. The Tukey results indicate that at small problem sizes there is no significant difference between 3-OPT and SA though there is a significant difference between 3-opt and SA with the Construction heuristic (see Tables 5.26 and 5.29). As problem size increases the Construction heuristic reduces more changeover time than both 3-OPT and SA. Again we see the superior performance of the
Construction heuristics performance under large problems. The following are general conclusions:

1. In a manufacturing environment characterized by high CV and \( w = \) changeover, there is a significant interaction at \( p = .05 \) between heuristics and problem size for percent improvement in changeover time. The results indicate that there is no significant difference between 3-OPT and SA at small problem sizes though there is a significant difference between both 3-OPT and SA with the Construction heuristic. Performance increases for all heuristics as problem size increases. In fact the Construction heuristic outperforms 3-opt and SA under large problem settings.

2. When measuring the percent improvement in lateness performance is significantly worse than the initial MPS under small problems and large problems.

5.7 The effect of operating conditions upon the relative performance of scheduling heuristics. Tradeoff parameter = equal

A two-way ANOVA design was used to test the interaction of CV and problem size with heuristics when a decision maker places equal weight on both criteria. This test was run under every combination of problem size and coefficient of variation of the changeover matrix. The Tukey pairwise means test will be used to determine the level of significance between the scheduling heuristics. Each section that follows will further explore these interactions.
5.7.1 The interaction of CV and heuristics at small problem sizes.

The results of this experiment can be seen in Tables 5.32 and 5.35 for percent improvement changeover time and percent improvement in lateness respectively. The interaction between CV and heuristics is significant at (p = .05) for percent improvement in changeover time and percent improvement in lateness. The results are presented in Figures 5.27 and 5.28. The Tukey pairwise means test (Table 5.33) indicates there is no significant difference in percent improvement in changeover time between all three heuristics at a low CV setting. Though at a high CV setting (Table 5.34) there is a significant difference at (p = .05) between both 3-OPT and SA with Construction though not between 3-OPT and SA. It is evident in Figure 5.27 that as CV increases there is a significant reduction in changeover time for 3-OPT and SA, though the performance of the Construction heuristic increases only slightly.

For percent improvement in lateness the same result holds true. The Tukey pairwise means test (Table 5.36) indicates there is no significant difference in percent improvement in lateness at (p = .05) between all three heuristics at a low CV setting. Though at a high CV setting (Table 5.37) there is a significant difference at (p = .05) between both 3-OPT and SA with Construction though not between 3-OPT and SA. Figure 30 shows that as CV increases there is a significant reduction in lateness time for 3-OPT and SA, though the performance of the Construction decreases slightly but not statistically significant. For both of the performance measures the results indicate that:
1. In a manufacturing environment characterized by small problem size and \( w = \text{equal} \), there is a significant interaction at \( p = .05 \) between heuristics and CV for percent improvement in changeover time. The results indicate there is no significant difference between heuristics at a low CV, though a significant difference between both 3-OPT and SA with Construction at a high CV. Performance increases for 3-OPT and SA as CV increases, but for the Construction heuristic performance holds relatively constant.

2. In a manufacturing environment characterized by small problem size and \( w = \text{equal} \), there is a significant interaction at \( p = .05 \) between heuristics and CV for percent improvement in lateness. The results indicate there is no significant difference in percent improvement in lateness among the three scheduling heuristics at a low CV setting. Though at a high CV setting there is a significant difference between both 3-OPT and SA with Construction.

5.7.2 The interaction of CV and heuristics at large problem sizes.

Results from this experiment can be seen in Tables 5.38 and 5.41. The ANOVA results indicate that the interaction between heuristics and CV is significant at \( p = .05 \) for percent improvement in changeover time but the interaction is not significant at \( p = .05 \) for percent improvement in lateness. The Tukey pairwise comparison (Table 5.39) indicates there is no significant difference in percent improvement in changeover time between 3-OPT and SA at a low CV setting though there is a significant difference between both 3-OPT and SA with Construction (see Figure 5.29). Results from Table 5.40 indicates there is no significant difference between all three heuristics for percent improvement in changeover time at a high CV setting (see Figure 5.29).

For percent improvement in lateness the results indicate there is a significant difference (\( p = .05 \)) in percent improvement in lateness between both 3-OPT and SA with Construction at a low CV setting, though there is no significant difference between 3-OPT
with SA. The same results hold for a high CV setting (See Figure 5.30). The following are general conclusions from this analysis.

1. In a manufacturing environment characterized by large problem size and \( w = \text{equal} \), there is a significant interaction at \( p = .05 \) between heuristics and CV for percent improvement in changeover time. The results indicate there is no significant difference between all three heuristics at either a low or high CV setting. Percent improvement in changeover time increases for all three heuristics as CV increases.

2. In a manufacturing environment characterized by large problem size and \( w = \text{equal} \), there is no interaction between heuristics and CV for percent improvement in lateness. The results indicate that both 3-OPT and SA get more improvement in lateness than the Construction heuristic for both low and high CV. Though, performance increases for all three heuristics as CV increases.

5.7.3 The interaction of problem size and heuristics at low coefficient of variation.

The results of the ANOVA analysis are shown in Tables 5.44 and 5.45 for percent improvement in changeover time and percent improvement in lateness respectively. The results indicate that the interaction between problem size and heuristic is significant at \( p = .05 \) for both percent improvement in changeover time and percent improvement in lateness. Thus the effect of problem size on percent improvement in changeover time, and percent improvement in lateness is not the same for all heuristics. Under small problem size environments there is no significant difference in percent improvement in changeover time between heuristics (see Table 5.33). As problem size increases there is a significant difference between both 3-OPT and SA with Construction though there is no significant
difference between 3-OPT and SA (see Table 5.39). Under large problems the
Construction heuristic gets slightly more improvement in changeover time (See Figure
5.31).

For percent improvement in lateness under small problem size environments there is
no significant difference between all three heuristics at (p = .05) (see Table 5.36). As
problem size increases there is a significant difference between both 3-OPT and SA with
Construction (see Table 5.42). As problem size gets larger the Construction heuristic’s
performance actually decreases. Though the lateness measurement is not significantly
worse than the initial MPS (see Figure 5.32). The following general conclusions can be
made from the statistical results:

1. In a manufacturing environment characterized by low CV and w = equal, there is a significant interaction at p = .05 between heuristics and problem size for percent improvement in changeover time. The results indicate there is no significant difference between heuristics at small problem sizes though a significant difference between both 3-OPT and SA with Construction at large problem sizes. Performance decreases for both 3-OPT and SA as problem size increases though performance holds relatively constant for Construction.

2. In a manufacturing environment characterized by low CV and w = equal, there is a significant interaction at p = .05 between heuristics and problem size for percent improvement in lateness. The results indicate there is no significant difference between heuristics at small problem sizes and a significant difference between both 3-OPT and SA with Construction at large problem sizes. Performance increases significantly for both 3-OPT and SA as problem size increases though performance holds relatively constant for Construction.
5.7.4 The interaction of problem size and heuristics at high coefficient of variation.

The results of the ANOVA analysis are shown in Tables 5.46 and 5.47. The results indicate the interaction between problem size and heuristics is significant at \( p = .05 \) for percent improvement in changeover time but \textit{not} for percent improvement in lateness. The results (Table 5.34) indicate that under small problem sizes there is a significant difference in percent improvement in changeover time between both 3-OPT and SA with Construction though there is \textit{no} significant difference between 3-OPT and SA. Under large problem sizes (see Table 5.40) there is no significant difference between all three heuristics at \( p = .05 \). Performance actually improves for the Construction heuristic as problem size increases and gets worse for 3-OPT and SA with respect to percent improvement in changeover time (See Figure 5.33).

For percent improvement in lateness, as problem size increases performance for all three heuristics increase, though 3-OPT and SA significantly outperform Construction at both levels of problem size (See Tables 5.37, 5.43 and Figure 5.34). The following are general conclusions from the results above.

1. In a manufacturing environment characterized by low CV and \( w = \text{equal} \), there is a significant interaction at \( p = .05 \) between heuristics and problem size for percent improvement in changeover time. The results indicate that there is no significant difference between 3-OPT and SA at small problem sizes though there is a significant difference between both 3-OPT and SA with the Construction heuristic. Performance decreases for 3-OPT and SA as problem size increases though performance increases for Construction. Thus at large problem sizes there is no significant difference between all three heuristics.
2. In a manufacturing environment characterized by low CV and \( w = \) equal, there is a significant interaction at \( p = .05 \) between heuristics and problem size for percent improvement in lateness. As problem size increases percent improvement in lateness increases. The results indicate there is no significant difference between 3-OPT and SA at small problem sizes though there is a significant difference between both 3-OPT and SA with Construction. At large problem sizes there is no significant difference between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction.

5.8 The effect of operating conditions upon the relative performance of heuristics

Tradeoff parameter = lateness

A two-way ANOVA design was used to test the interaction of CV and problem size with heuristics when a decision maker places 99% weight on reducing lateness. This test was run under every combination of problem size and coefficient of variation of the changeover matrix. The Tukey pairwise means test will be used to determine the level of significance between the scheduling heuristics. Each section that follows will further explore these interactions.

5.8.1 The interaction of CV and heuristics at small problem sizes.

The results of the two-way ANOVA are presented in Tables 5.48 and 5.51 for percent improvement changeover time and percent improvement in lateness respectively. The interaction between CV and heuristics are significant at \( p = .05 \) for percent improvement in changeover time though not for percent improvement in lateness. The results are presented in Figures 5.35 and 5.36. The Tukey pairwise means tests (Table 5.49) indicates that there is no significant difference in percent improvement in changeover
time between all three heuristics at a low CV setting. Though at a high CV setting (Table 5.50) there is a significant difference at \( p = .05 \) between both 3-OPT and SA with Construction but not between 3-OPT and SA. It is evident in Figure 5.35 that as CV increases there is a significant reduction in changeover time for 3-OPT and SA, though the performance of the Construction heuristic holds relatively constant.

For percent improvement in lateness the Tukey pairwise means tests (Table 5.52) indicates under a low CV setting there is no significant difference in percent improvement in lateness at \( p = .05 \) between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction. Under a high CV setting (Table 5.53) there is a significant difference at \( p = .05 \) between both 3-OPT and SA with Construction but not between 3-OPT and SA. As CV increases there is a significant reduction in lateness time for 3-OPT and SA, and the performance of the Construction heuristic holds constant. Though the performance of the Construction heuristic is not statistically different than the initial MPS. The following are general conclusion from the analysis above.

1. In a manufacturing environment characterized by small problem size and \( w = \) lateness, there is a significant interaction at \( p = .05 \) between heuristic and CV for percent improvement in changeover time. The results indicate there is no significant difference between heuristics at a low CV, though a significant difference between both 3-OPT and SA with Construction at a high CV. Performance improves for both 3-OPT and SA with an increase in CV.
2. In a manufacturing environment characterized by small problem size and w = lateness, there is no significant interaction at p = .05 between heuristic and CV for percent improvement in lateness. The results indicate there is no significant difference between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction at both low and high CV settings. Performance improves for both 3-OPT and SA with an increase in CV.

5.8.2 The interaction of CV and heuristics at large problem sizes.

Results from the two-way ANOVA are presented in Tables 5.54 and 5.57. The ANOVA results indicate that the interaction between heuristics and CV is significant at p = .05 for both percent improvement in changeover time and percent improvement in lateness. The Tukey pairwise comparison (Table 5.55) indicates that at a low CV setting there is no significant difference in percent improvement in changeover time between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction. Results (Table 5.56) also indicate that at a high CV setting there is no significant difference between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction. Figure 5.37 shows that as CV increases the percent improvement in changeover time for 3-OPT and SA, though the Construction heuristic performance holds relatively constant.

For percent improvement in lateness the results indicate under a low CV setting (Table 5.58) there is a significant difference in percent improvement in lateness between both 3-OPT and SA with Construction though there is no significant difference between 3-OPT with SA. The same results hold for a high CV setting (Table 5.59) Figure 5.38 shows that as CV increases the percent improvement in lateness increases for 3-OPT and
SA, though performance for the Construction heuristics decreases slightly but is not significantly different (at $p = .05$) from the initial MPS. The following are general conclusions from this analysis.

1. In a manufacturing environment characterized by large problem size and $w = \text{lateness}$, there is a significant interaction at $p = .05$ between heuristic and CV for percent improvement in changeover time. The results indicate under low and high settings for CV there is no significant difference between 3-OPT and SA, though there is a significant difference between both 3-OPT and SA with Construction. As CV increases performance for both 3-OPT and SA increases though performance for Construction decreases slightly.

2. In a manufacturing environment characterized by large problem size and $w = \text{lateness}$, there is a significant interaction at $p = .05$ between heuristic and CV for percent improvement in lateness. The results indicate that there is no significant difference between 3-OPT and SA at both levels of CV, though there is a significant difference between both 3-OPT and SA with Construction at both levels of CV. As CV increases performance for both 3-OPT and SA increases though performance for Construction decreases slightly.

5.8.3 The interaction of problem size and heuristics at low coefficient of variation.

The results of the two-way ANOVA analysis are shown in Table 5.60 for percent improvement in lateness. There is no analysis for percent improvement in changeover time because in OEN 3 there is no improvement in changeover time against the initial MPS (see Figure 5.39). For percent improvement in lateness the results indicate that the interaction between problem size and heuristic is not significant at $p = .05$. Thus the effect of problem size on percent improvement in lateness is the same for all heuristics. As problem size increases percent improvement in lateness increases.
Under small problem size environments there is no significant difference between 3-OPT and SA, though there is a significant difference at $p = .05$ between both 3-OPT and SA with Construction (see Table 5.52). Under small problem sizes both 3-OPT and SA produce significantly better results than the initial MPS, though the Construction heuristic is not significantly different than the initial MPS.

Under large problem size environments there is no significant difference at $p = .05$ between 3-OPT and SA, though there is a significant difference between both 3-OPT and SA with Construction (see Table 5.58). It is interesting to note that as problem size increases the performance of all three heuristics increase though the Construction heuristic is still not significantly different than the initial MPS (See Figure 5.40). The following general conclusions can be made from the statistical results:

1. **In a manufacturing environment characterized by low CV and $w =$ lateness, there is no significant interaction between heuristic and problem size for percent improvement in changeover time. There is no significant increase in changeover time for all three heuristics against the initial MPS.**

2. **In a manufacturing environment characterized by low CV and $w =$ lateness, there is no significant interaction between heuristic and problem size for percent improvement in changeover time. The results indicate that under small problem size there is no significant difference between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with Construction. Under large problem sizes there is no significant difference between 3-OPT and SA, though there is a significant difference between both 3-OPT and SA with Construction. As problem size increases percent improvement in lateness increases for all three heuristics.**
5.8.4 The interaction of problem size and heuristics at high coefficient of variation.

The results of the two-way ANOVA analysis are shown in Tables 5.61 and 5.62. The results indicate the interaction between problem size and heuristics is not significant at \( p = .05 \) for percent improvement in changeover though the interaction is significant for percent improvement in lateness. The Tukey results (see Tables 5.50 and 5.56) indicate that at both levels of problem size there is no significant difference in percent improvement in changeover time between 3-OPT and SA though there is a significant difference between both 3-OPT and SA with the Construction heuristic. As problem size increases percent improvement in changeover time decreases for all three heuristics. For 3-OPT and SA performance is still significantly better than the initial MPS. For the Construction heuristic there is no significant difference in performance relative to the initial MPS at either low or high problem size (See Figure 5.41).

For percent improvement in lateness, Tukey results (see Table 5.53) indicate under small problem size there is no significant difference at \( p = .05 \) in performance between 3-OPT with SA, though there is a significant difference in performance between both 3-OPT and SA with Construction. As problem size increases performance for both 3-OPT and SA hold relatively constant. For the Construction heuristic performance actually increases though still significantly different from both 3-OPT and SA (See Figure 5.42). The following are general observations from the analysis above.
1. In a manufacturing environment characterized by high CV and \( w = \) lateness, there is no significant interaction between heuristics and problem size for percent improvement in changeover time. The results indicate there is no significant difference between 3-OPT and SA at both levels of problem size though there is a significant difference between both 3-OPT and SA with Construction at both levels of problem size. Performance decreases for all three heuristics as problem size increases.

2. In a manufacturing environment characterized by high CV and \( w = \) lateness, there is a significant difference at \( p = .05 \) between heuristic and problem size for percent improvement in lateness. The results indicate there is no significant difference between 3-OPT and SA at both levels of problem size though there is a significant difference between both 3-OPT and SA with Construction at both levels of problem size. Performance is relatively constant for 3-OPT and SA and increases slightly for Construction.

5.9 Operating performance of scheduling heuristics against the optimal solution

In this section we will focus on solution quality. Solution quality is defined to be the percent gap between the heuristic solution and the optimal solution for a given schedule. For the rest of this section we will refer to solution quality as heuristic gap. The results in this section will be analyzed under the same format as above except for one exception. As mentioned in chapter 4 there will only be six different operating environments. This is because only one level of problem size was used in this design. An optimal solution could not be found for problems of 100 orders.

5.9.1 The effect of tradeoff parameter on performance

A completely randomized full factorial ANOVA design was used to determine the effect of the tradeoff parameter on heuristic gap. This design is averaged across all heuristics and coefficient of variation of changeover matrices. The ANOVA results are
shown in Table (5.63). The results indicate that there is a significant difference in heuristic gap at \( p = .05 \) at each level of the tradeoff parameter. Looking further at the results, it is evident that the Construction heuristic does significantly worse than 3-OPT and SA when both criteria have equal weights and when 99% of weight is placed on lateness (See Figure 5.43). The solution quality of 3-OPT and SA is very good as both average 2% of the optimal solution across all levels of the tradeoff parameter.

5.10  The effect of operating conditions at tradeoff parameter = changeover

The experimental results in this section show the effect of (i) scheduling heuristics, (ii) changes in CV and (iii) interaction between scheduling heuristics and CV on performance when 99% of weight is placed on reducing changeover time.

5.10.1 Main effect of scheduling heuristic

The results in Table 5.64 show the performance of the three scheduling heuristics under both low and high CV. The Two-way ANOVA results shown in Table 5.65 indicate the main effect (scheduling heuristic) is not significant at \( p = .05 \). The 3-OPT scheduling heuristic produces schedules that average 1.72% over optimum for changeover time as shown in Table 5.64.

5.10.2 Main effect of CV

The two-way ANOVA results shown in Table 5.65 indicate that the main effect of CV is significant at \( p = .05 \) for heuristic gap. The results in Table 5.64 indicate that
solution quality declines as CV increases. Thus as CV increases the problems become more difficult for heuristics to solve. Though results are very favorable to the initial MPS.

5.10.3 Interaction Between Heuristics and CV

The ANOVA results in Table 5.65 indicate that the Heuristic x CV interaction is not significant at the (p = .05) level. As shown in Figure 5.44 the effect of CV on performance is the same for all three heuristics. Solution quality declines for all three heuristics as CV increases.

5.11 The effect of operating conditions at tradeoff parameter = equal

This section gives experimental results for the main effect of (i) scheduling heuristics (ii) coefficient of variation and (iii) interaction between scheduling heuristic and coefficient of variation when equal weights are placed on both criteria.

5.11.1 Main effect of scheduling heuristic

The results shown in Table 5.64 show the performance of the three scheduling heuristics. The results indicate that scheduling heuristics produce significantly different results with respect to Heuristic Gap % when the decision maker places equal weight on reducing changeover time and reducing lateness. The ANOVA results shown in Table 5.66 indicate that the main effect (scheduling heuristic) is significant at (p = .05). The Tukey pairwise comparison test (Table 5.67) show that there is a significant difference between both 3-OPT and SA with Construction, though there is not a significant
difference between 3-OPT and SA. The SA heuristic produces schedules that average 1.41% over the optimum solution as shown in Table 5.64.

5.11.2 Main effect of CV

The two-way ANOVA results shown in Table 5.66 indicate the main effect of CV is significant at p = .05. The results in Table 5.64 indicate that solution quality declines as CV increases. Again we similar results as an earlier section when 99% of weight is placed on changeover time. That is, problems become more difficult when CV increases. Though scheduling heuristics are favorable when we measure performance against the initial MPS.

5.11.3 Interaction Between Heuristics and CV

The two-way ANOVA results in Table 5.66 indicate that the Heuristic x CV interaction is significant at the (p = .05) level. As shown in Figure 5.45 the effect of CV on performance is not the same for all three heuristics. Solution quality for the Construction heuristic degrades at a higher rate than 3-OPT and SA. Though all three heuristics performance decreases as CV increases.

5.12 The effect of operating conditions at tradeoff parameter = lateness

This section gives experimental results for the main effect of (i) scheduling heuristics (ii) coefficient of variation and (iii) interaction between scheduling heuristic and coefficient of variation when 99% of weight is placed on reducing lateness.
5.12.1 Main effect of scheduling heuristic

The results shown in Table 5.64 shows the performance of the three scheduling heuristics. The two-way ANOVA results shown in Table 5.68 indicate that the main effect (scheduling heuristic) is significant at \( p = .05 \). The Tukey pairwise comparison test (Table 5.69) show that there is a significant difference between both 3-OPT and SA with Construction, though there is not a significant difference between 3-OPT and SA. The SA heuristic produces schedules that average 1.13\% over the optimum solution. Solution quality actually improves as more weight is placed on lateness. This is because the initial MPS is an Earliest Due Date schedule which minimizes tardiness. Tardiness is one component of lateness. Thus the number of iterations to improve the schedule should be minimal.

5.12.2 Main effect of CV

The two-way ANOVA results shown in Table 5.68 indicate the main effect of CV is significant at \( p = .05 \). The results in Table 5.64 indicate that solution quality declines as CV increases.

5.12.3 Interaction between heuristics and CV

The two-way ANOVA results in Table 5.68 indicate that the Heuristic x CV interaction is significant at the \( p = .05 \) level. As shown in Figure 5.46 the effect of CV on performance is not the same for all three heuristics. Solution quality for the
Construction heuristic degrades at a higher rate than 3-OPT and SA. The following are general observations from the previous sections.

1. In a manufacturing environment characterized by both low and high CV, solution quality increases as more weight is placed on reducing lateness.

2. In a manufacturing environment characterized by sequence dependent changeovers, solution quality declines as CV increases.

3. In a manufacturing environment characterized by low and high CV and 99% of weight on reducing changeover time there is no significant difference in performance between all three heuristics.

4. In a manufacturing environment characterized by low and high CV, and equal weight placed on both criteria, there is a significant difference between both 3-OPT and SA with Construction at \( p = 0.05 \) for heuristic gap.
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<tr>
<th></th>
<th>CV</th>
<th>2-OPT</th>
<th>SA</th>
<th>Construction</th>
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<td>9</td>
<td>12</td>
</tr>
</tbody>
</table>

Note: \( \omega_{cr} \) is the weight on reducing changeover time, \( \omega_{eq} \) is where the weight is equally distributed between both criteria, and \( \omega_{eq} \) is when 99% of the weight is placed on reducing interest.

Table 5.1: Operating environments

116
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<th>Size</th>
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<td>(\omega_{equal})</td>
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</tr>
</tbody>
</table>

* Note: Borders indicate where there is a significant difference in changeover time between the MPS and individual scheduling heuristics. The shade borders indicate a significant degradation in changeover time.

**Table 5.2** Results of the T Tests on the initial MPS changeover time vs. final MPS changeover time
<table>
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<tr>
<th>Size</th>
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<th></th>
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<th>SA</th>
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<th>Const.</th>
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<td></td>
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<td>(\bar{\omega}_{equal})</td>
<td>(\bar{\omega}_{late})</td>
<td>(\bar{\omega}_{c/o})</td>
<td>(\bar{\omega}_{equal})</td>
<td>(\bar{\omega}_{late})</td>
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* Note: Borders indicate where there is a significant difference in lateness time between the MPS and individual scheduling heuristics. The shaded borders indicate a significant degradation in lateness time.

Table 5.3 Results of the T Tests on the initial MPS lateness vs. final MPS lateness
<table>
<thead>
<tr>
<th>Size</th>
<th>CV</th>
<th>Perform</th>
<th>3-OPT</th>
<th>SA</th>
<th>Construction</th>
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</thead>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Ωc/o</td>
<td>Ωequal</td>
<td>Ωlate</td>
</tr>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>Low</td>
<td>c/o</td>
<td>31.4%</td>
<td>5.1%</td>
<td>32.2%</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>9.5%</td>
<td></td>
</tr>
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<td></td>
<td>High</td>
<td>c/o</td>
<td>51.6%</td>
<td>52.3%</td>
<td>31.9%</td>
</tr>
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<td></td>
<td>lateness</td>
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<td>57.6%</td>
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<td>c/o</td>
<td>71.4%</td>
<td>59.6%</td>
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<td>46%</td>
<td>45.6%</td>
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<td>c/o</td>
<td>76.7%</td>
<td>22.3%</td>
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<td>70.1%</td>
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Note: The shaded area are positively statistically significant at p = .05

Table 5.4 Percentage improvement in total changeover time and total lateness time
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<thead>
<tr>
<th>Source</th>
<th>F-ratio</th>
<th>P-value</th>
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</thead>
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<tr>
<td>Weight</td>
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</table>

**Table 5.5** Main effect of tradeoff parameter (percent improvement in changeover time)

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<th>$W_{late}$</th>
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**Table 5.6** Tukey pairwise comparison probabilities

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<th>Source</th>
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<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>405.9</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.7** Main effect of tradeoff parameter (percent improvement in lateness)

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<th>$W_{equal}$</th>
<th>$W_{late}$</th>
</tr>
</thead>
<tbody>
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**Table 5.8** Tukey pairwise comparison probabilities

120
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<tr>
<th>Source</th>
<th>F-ratio</th>
<th>p value</th>
</tr>
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<td>.011</td>
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<td>Heu x Size</td>
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<td>CV x Size</td>
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**Table 5.9** Main effects at tradeoff parameter = changeover (percent improvement in changeover time)

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<th>Const.</th>
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</thead>
<tbody>
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</tr>
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<td>Const</td>
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<td>.761</td>
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</table>

**Table 5.10** Tukey pairwise comparison probabilities

<table>
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<th>CV(HIGH)</th>
<th>AVG.</th>
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<tr>
<td>Large</td>
<td>71.5 %</td>
<td>76.4 %</td>
<td>74.0 %</td>
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<td>Small</td>
<td>29.5 %</td>
<td>41.9 %</td>
<td>35.7 %</td>
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</table>

**AVG.**

|         | 50.5 %  | 59.2 % |

Note: These results are averaged across all heuristics.

**Table 5.11** Percent improvement in changeover time
<table>
<thead>
<tr>
<th>Source</th>
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<th>p value</th>
</tr>
</thead>
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<tr>
<td>Heu x CV</td>
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<tr>
<td>CV x Size</td>
<td>5.9</td>
<td>.017</td>
</tr>
</tbody>
</table>

Table 5.12 Main effects at tradeoff parameter = equal (Percent improvement in changeover time)

<table>
<thead>
<tr>
<th></th>
<th>3-OPT</th>
<th>SA</th>
<th>Const.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-OPT</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.924</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>.000</td>
<td>.00</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.13 Tukey pairwise comparison probabilities

<table>
<thead>
<tr>
<th>Source</th>
<th>F-ratio</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>46.43</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>39.96</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>14.94</td>
<td>.000</td>
</tr>
<tr>
<td>Heu x CV</td>
<td>3.9</td>
<td>.023</td>
</tr>
<tr>
<td>Heu x Size</td>
<td>3.22</td>
<td>.043</td>
</tr>
<tr>
<td>CV x Size</td>
<td>.069</td>
<td>.793</td>
</tr>
</tbody>
</table>

Table 5.14 Main effects at tradeoff parameter = equal (percent improvement in lateness)

<table>
<thead>
<tr>
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<th>SA</th>
<th>Const</th>
</tr>
</thead>
<tbody>
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<td></td>
</tr>
<tr>
<td>SA</td>
<td>.788</td>
<td>1.0</td>
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</tr>
<tr>
<td>Const</td>
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<td>.00</td>
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</tr>
</tbody>
</table>

Table 5.15 Tukey pairwise comparison probabilities
<table>
<thead>
<tr>
<th></th>
<th>CV(LOW)</th>
<th>CV(HIGH)</th>
<th>AVG.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (Large)</td>
<td>-2.5 %</td>
<td>19.0 %</td>
<td>8.3 %</td>
</tr>
<tr>
<td>Size (Small)</td>
<td>4.2 %</td>
<td>36.0 %</td>
<td>22.1 %</td>
</tr>
<tr>
<td>AVG.</td>
<td>.85 %</td>
<td>27.5 %</td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.16** Percent improvement in changeover time for (W = equal)

<table>
<thead>
<tr>
<th></th>
<th>CV(LOW)</th>
<th>CV(HIGH)</th>
<th>AVG.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (Large)</td>
<td>27.8 %</td>
<td>53.5 %</td>
<td>40.1 %</td>
</tr>
<tr>
<td>Size (Small)</td>
<td>10.2 %</td>
<td>38.2 %</td>
<td>24.2 %</td>
</tr>
<tr>
<td>AVG.</td>
<td>19.0 %</td>
<td>45.9 %</td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.17** Percent improvement in lateness time (W = equal)
<table>
<thead>
<tr>
<th>Source</th>
<th>F-ratio</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>5.42</td>
<td>.006</td>
</tr>
<tr>
<td>CV</td>
<td>9.05</td>
<td>.003</td>
</tr>
<tr>
<td>Size</td>
<td>37.7</td>
<td>.000</td>
</tr>
<tr>
<td>Heu x Cv</td>
<td>10.42</td>
<td>.000</td>
</tr>
<tr>
<td>Heu x Size</td>
<td>.421</td>
<td>.657</td>
</tr>
<tr>
<td>CV x Size</td>
<td>4.05</td>
<td>.047</td>
</tr>
</tbody>
</table>

Table 5.18 Main effects at tradeoff parameter = late (percent improvement in changeover time)

<table>
<thead>
<tr>
<th></th>
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<th>SA</th>
<th>Const.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-OPT</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.996</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>.016</td>
<td>.013</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.19 Tukey pairwise comparison probabilities

<table>
<thead>
<tr>
<th>Source</th>
<th>F-ratio</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>55.18</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>1.46</td>
<td>.023</td>
</tr>
<tr>
<td>Size</td>
<td>1.61</td>
<td>.021</td>
</tr>
<tr>
<td>Heu x CV</td>
<td>22.9</td>
<td>.000</td>
</tr>
<tr>
<td>Heu x Size</td>
<td>10.66</td>
<td>.000</td>
</tr>
<tr>
<td>CV x Size</td>
<td>24.78</td>
<td>.000</td>
</tr>
</tbody>
</table>

Table 5.20 Main effects at tradeoff parameter = late (percent improvement in lateness)

<table>
<thead>
<tr>
<th></th>
<th>3-OPT</th>
<th>SA</th>
<th>Const.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-OPT</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.949</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.21 Tukey pairwise comparison probabilities
<table>
<thead>
<tr>
<th></th>
<th>CV(LOW)</th>
<th>CV(HIGH)</th>
<th>AVG.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size (Large)</strong></td>
<td>-5.1 %</td>
<td>7.2 %</td>
<td>1.1 %</td>
</tr>
<tr>
<td><strong>Size (Small)</strong></td>
<td>-2.1 %</td>
<td>22.2 %</td>
<td>10.1 %</td>
</tr>
</tbody>
</table>

**AVG.**

-3.6 % 14.7 %

*Table 5.22* Percent improvement in changeover time for $w = \text{lateness}$

<table>
<thead>
<tr>
<th></th>
<th>CV(LOW)</th>
<th>CV(HIGH)</th>
<th>AVG.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size (Large)</strong></td>
<td>35.1 %</td>
<td>40.0 %</td>
<td>37.6 %</td>
</tr>
<tr>
<td><strong>Size (Small)</strong></td>
<td>3.5 %</td>
<td>34.6 %</td>
<td>19.1 %</td>
</tr>
</tbody>
</table>

**AVG.**

19.3 % 37.3 %

*Table 5.23* Percent improvement in lateness time for $w = \text{lateness}$
<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.002</td>
</tr>
<tr>
<td>H x CV</td>
<td>.046</td>
</tr>
</tbody>
</table>

**Table 5.24** Full factorial model (CV vs. Heur.) For Small Prob. Size and W = C/O

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
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<td></td>
</tr>
<tr>
<td>SA</td>
<td>.981</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.302</td>
<td>.225</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.25** Tukey pairwise comparison probabilities (CV = Low; Size = Small)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.986</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.006</td>
<td>.009</td>
<td>1.0</td>
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</tbody>
</table>

**Table 5.26** Tukey pairwise comparison probabilities (CV = High; Size = Small)

<table>
<thead>
<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.048</td>
</tr>
</tbody>
</table>

**Table 5.27** Full factorial model (CV vs. Heuristic) For Large Prob. Size and W = C/O

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.000</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.28** Tukey pairwise comparison probabilities (CV = Low; Size = Large)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.003</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.008</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.29** Tukey pairwise comparison probabilities (CV = High; Size = Large)
<table>
<thead>
<tr>
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<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.003</td>
</tr>
<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.30** Full factorial model (Size vs. Heuristic) For CV = low and W = C/O

<table>
<thead>
<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.077</td>
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<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.31** Full factorial model (Size vs. Heuristic) For CV = high W = C/O
<table>
<thead>
<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.32** Full factorial model (CV vs. Heuristic) For Small Problem Size and Weight = Equal (Percent improvement in changeover time)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>1.0</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.871</td>
<td>.702</td>
<td>1.0</td>
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</table>

**Table 5.33** Tukey pairwise comparison probabilities (CV = Low; Size = Small)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
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<td></td>
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<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.34** Tukey pairwise comparison probabilities (CV = High; Size = Small)

<table>
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<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
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</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.35** Full factorial model (CV vs. Heuristic) For Small Problem Size and Weight = Equal (percent improvement in lateness)

<table>
<thead>
<tr>
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<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.774</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>1.0</td>
<td>.393</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.36** Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Small)

<table>
<thead>
<tr>
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<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.990</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.37** Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Small)

128
Table 5.38 Full factorial model (CV vs. Heuristic) For Large Problem Size and Weight = Equal (percent improvement in changeover time)

<table>
<thead>
<tr>
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<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
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</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.008</td>
</tr>
</tbody>
</table>

Table 5.39 Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Large)

<table>
<thead>
<tr>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.997</td>
<td>1.0</td>
</tr>
<tr>
<td>Cons</td>
<td>.019</td>
<td>.016</td>
</tr>
</tbody>
</table>

Table 5.40 Tukey pairwise comparison probabilities (CV = High; Size = Large)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.956</td>
</tr>
</tbody>
</table>

Table 5.41 Full factorial model (CV vs. Heuristic) For Large Problem Size and Weight = Equal (percent improvement in lateness)

<table>
<thead>
<tr>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
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<tr>
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<td>.998</td>
<td>1.0</td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
</tr>
</tbody>
</table>

Table 5.42 Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Large)

<table>
<thead>
<tr>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.955</td>
<td>1.0</td>
</tr>
<tr>
<td>Cons</td>
<td>.001</td>
<td>.000</td>
</tr>
</tbody>
</table>

Table 5.43 Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Large)

<table>
<thead>
<tr>
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<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.968</td>
</tr>
<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.037</td>
</tr>
</tbody>
</table>

**Table 5.44** Full factorial model (Size vs. Heuristic) For CV = low and W = equal (percent improvement in changeover time)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.45** percent improvement in lateness

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.46** Full factorial model (Size vs. Heuristic) For CV = high and W = Equal (percent improvement in changeover time)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>.038</td>
</tr>
<tr>
<td>H x Size</td>
<td>.991</td>
</tr>
</tbody>
</table>

**Table 5.47** percent improvement in lateness
<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.103</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.016</td>
</tr>
</tbody>
</table>

Table 5.48  Full factorial model (CV vs. Heuristic) For Small Problem Size and W = Late (percent improvement in changeover time)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.968</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.355</td>
<td>.245</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.49  Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Small)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.993</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.032</td>
<td>.024</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.50  Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Small)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.001</td>
</tr>
<tr>
<td>H x CV</td>
<td>.082</td>
</tr>
</tbody>
</table>

Table 5.51  Full factorial model (CV vs. Heuristic) For Small Problem Size and W = Late (percent improvement in lateness)

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.722</td>
<td>1.0</td>
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</tr>
<tr>
<td>Cons</td>
<td>.052</td>
<td>.013</td>
<td>1.0</td>
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</table>

Table 5.52  Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Small)

<table>
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<tr>
<th></th>
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<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
</tr>
<tr>
<td>SA</td>
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<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.001</td>
<td>.001</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 5.53  Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Small)
<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>H x CV</td>
<td>.000</td>
</tr>
</tbody>
</table>

*Table 5.54 Full factorial model (CV vs. Heuristic) For Size = Large and W = Late (percent improvement in changeover time)*

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.739</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.056</td>
<td>.01</td>
<td>1.0</td>
</tr>
</tbody>
</table>

*Table 5.55 Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Large)*

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.940</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

*Table 5.56 Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Large)*

<table>
<thead>
<tr>
<th></th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.001</td>
</tr>
<tr>
<td>H x CV</td>
<td>.000</td>
</tr>
</tbody>
</table>

*Table 5.57 Full factorial model (CV vs. Heuristic) For Size = Large and W = Late (percent improvement in lateness)*

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.972</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.003</td>
<td>.002</td>
<td>1.0</td>
</tr>
</tbody>
</table>

*Table 5.58 Tukey pairwise comparison probabilities (Heuristics CV = Low; Size = Large)*

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.999</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

*Table 5.59 Tukey pairwise comparison probabilities (Heuristics CV = High; Size = Large)*
<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
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</tr>
<tr>
<td>Size</td>
<td>.000</td>
</tr>
<tr>
<td>H x Size</td>
<td>.871</td>
</tr>
</tbody>
</table>

**Table 5.60** Full factorial model (Size vs. Heuristic) For CV = Low and W = Late (percent improvement in lateness)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>.012</td>
</tr>
<tr>
<td>H x Size</td>
<td>.545</td>
</tr>
</tbody>
</table>

**Table 5.61** Full factorial model (Size vs. Heuristic) For CV = High and W = Late (percent improvement in changeover time)

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>Size</td>
<td>.002</td>
</tr>
<tr>
<td>H x Size</td>
<td>.000</td>
</tr>
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</table>

**Table 5.62** Full factorial model (Size vs. Heuristic) For CV = High and W = Late (percent improvement in lateness)
<table>
<thead>
<tr>
<th>Source</th>
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</thead>
<tbody>
<tr>
<td>Weight</td>
<td>.047</td>
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</table>

**Table 5.63** Main Effect of Tradeoff Parameter: Heuristic Gap%

<table>
<thead>
<tr>
<th></th>
<th>3-OPT</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\omega_{o/o}$</td>
<td>$\omega_{equal}$</td>
<td>$\omega_{late}$</td>
<td>$\omega_{o/o}$</td>
<td>$\omega_{equal}$</td>
<td>$\omega_{late}$</td>
<td>$\omega_{o/o}$</td>
<td>$\omega_{equal}$</td>
</tr>
<tr>
<td><strong>CV_low</strong></td>
<td>.95%</td>
<td>.91%</td>
<td>.74%</td>
<td>1.03%</td>
<td>.87%</td>
<td>.61%</td>
<td>1.46%</td>
<td>2.13%</td>
</tr>
<tr>
<td><strong>CV_high</strong></td>
<td>2.48%</td>
<td>2.03%</td>
<td>1.76%</td>
<td>2.98%</td>
<td>1.95%</td>
<td>1.65%</td>
<td>3.57%</td>
<td>8.68%</td>
</tr>
<tr>
<td><strong>Means</strong></td>
<td>1.72%</td>
<td>1.47%</td>
<td>1.25%</td>
<td>2.0%</td>
<td>1.41%</td>
<td>1.13%</td>
<td>2.52%</td>
<td>5.4%</td>
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</table>

**Table 5.64** Experimental Results (Average Heuristic Gap)
<table>
<thead>
<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
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</tr>
<tr>
<td>CV</td>
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<tr>
<td>CV x Heu</td>
<td>.083</td>
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</table>

**Table 5.65 ANOVA Result: Tradeoff Parameter = Changeover**

<table>
<thead>
<tr>
<th>Source</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
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</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>CV x Heu</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.66 ANOVA Result: Tradeoff Parameter = Equal**

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.981</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
</tr>
</tbody>
</table>

**Table 5.67 Tukey Pairwise Comparison Probabilities**

<table>
<thead>
<tr>
<th>Source</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>.000</td>
</tr>
<tr>
<td>CV</td>
<td>.000</td>
</tr>
<tr>
<td>CV x Heu</td>
<td>.000</td>
</tr>
</tbody>
</table>

**Table 5.68 ANOVA Result: Tradeoff Parameter = lateness**

<table>
<thead>
<tr>
<th></th>
<th>3-opt</th>
<th>SA</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-opt</td>
<td>1.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>.847</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>Cons</td>
<td>.000</td>
<td>.000</td>
<td>1.0</td>
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</tbody>
</table>

**Table 5.69 Tukey Pairwise Comparison Probabilities**
Figure 5.1 Main effect of tradeoff parameter
Figure 5.2 Main effect of tradeoff parameter
Figure 5.3 Main effect of \(cv\) at \(w = \text{changeover}\)

Figure 5.4 Main effect of problem size at \(w = \text{changeover}\)

Figure 5.5 CV x Problem size interaction \((w = \text{changeover})\)
Figure 5.7 Main effect of cv at (w = equal)

Figure 5.8 Main effect of cv at (w = equal)
Figure 5.9 Main effect of size at (w = equal)

Figure 5.10 Main effect of size at (w = equal)
Figure 5.11 CV x Problem Size Interaction (w = equal)

Figure 5.12 CV x Problem Size Interaction (w = equal)
Figure 5.13 Improvement in both criteria for OEN 5

Figure 5.14 Tradeoff of performance criteria for OEN 8
Figure 5.15 Main effect of size at (w = late)

Figure 5.16 Main effect of size at (w = late)
Figure 5.17 Main effect of cv at (w = late)

Figure 5.18 Main effect of cv at (w = late)
Figure 5.19 CV x Size interaction at (w = late)

Figure 5.20 CV x Size Interaction at (w = late)
Figure 5.21 improvement in both criteria for OEN 6

Figure 5.22 improvement in both criteria for OEN 12
Figure 5.23 heuristic vs cv; size = small & w = changeover

Figure 5.24 heuristic vs cv; size = large & w = changeover
Figure 5.25 heuristic vs. size; cv = low & w = changeover

Figure 5.26 heuristic vs size; cv = high & w = changeover
Figure 5.27 heuristic vs cv; size = small & w = equal

Figure 5.28 heuristic vs cv; size = small & w = equal
Figure 5.29 heuristic vs cv; size = large & w = equal

Figure 5.30 heuristic vs cv; size = large & w = equal
Figure 31: heuristic vs size; cv = low \& w = equal

Figure 5.32: heuristic vs size; cv = low \& weight = equal
Figure 5.33 heuristic vs size; $cv = high$ & $w = equal$

Figure 5.34 heuristic vs size; $cv = high$ & $w = equal$
Figure 5.35 heuristic vs cv; size = small & w = late

Figure 5.36 heuristic vs cv; size = small & w = late
Figure 5.37 heuristic vs cv; size = large & w = late

Figure 5.38 heuristic vs cv; size = large & w = late
Figure 5.39 heuristic vs size; cv = low & w = late

Figure 5.40 heuristic vs size; cv = low & w = late
Figure 5.41 heuristic vs size; cv = high & w = late

Figure 5.42 heuristic vs size
cv = high & weight = lateness
Figure 5.46 heuristic x cv interaction (w = late)
CHAPTER 6

SUMMARY AND SUGGESTIONS FOR FUTURE RESEARCH

This chapter summarizes the major contributions and findings of the dissertation and provides suggestions for extensions to the research initiated herein. The chapter begins with a summary of the major contributions provided by the dissertation. The major experimental findings of the data analysis are outlined next. The chapter concludes with some suggestions for advancing the work done in this study.

6.1 Major contributions of the dissertation

The primary contribution of this dissertation is the conceptual framework and methodology that has been established for studying Bi Criteria Master Production Scheduling with Sequence Dependent Changeovers. This was established by:

1. Developing a conceptual framework for formal analysis of the Master Production scheduling problem with sequence dependent changeovers and identifying the operational aspects of the problem.

2. Developing highly effective heuristics for scheduling problems of this nature.

3. Identified operating environments which effect decision making and determine direction of performance.

4. Identified important performance tradeoffs between changeover time and lateness that provide insight when making scheduling decisions.
6.2 Major experimental findings of the dissertation

The major findings of this dissertation concern: (1) The effect of operating conditions upon performance; (2) the relative operating performance of the various scheduling heuristics; (3) the performance tradeoffs that exist between changeover time and lateness when scheduling a problem of this nature. The experimental findings associated with each of these areas are discussed below.

6.3 The effect of problem size on performance

The operating conditions that exert the greatest influence upon the relative performance of the scheduling heuristics are the coefficient of variation of the changeover matrix and the number of orders in the MPS (problem size). The direction of influence (positive or negative) is dependent on the amount of weight the decision maker places on each criteria.

The interaction of the weight a decision maker places on each criteria and the levels of the operating factors influences the direction of performance. When a decision maker places 99% of weight on reducing changeover time the relative improvement in changeover time and lateness against the initial MPS increases in magnitude by 40% as problem size increases.

It was observed that the influence of problem size is reduced when equal weight is placed on both criteria and when 99% of weight is place on lateness. In these cases the percentage improvement in changeover time against the initial MPS decreases as problem size increases though there is still a significant improvement against the initial MPS. This is
because the increased weight placed on lateness restricts the scheduling heuristics from moving orders to far away from their original due date thus prohibiting like products from being sequenced together. This research finding is counter intuitive to most bi-criteria scheduling research where tradeoffs exists under conditions where the majority of weight is placed on one criteria.

Problem size also has a significant effect on the percentage improvement in lateness against the initial MPS under operating environments where equal weight is placed on both criteria and when 99% of weight is placed on improving lateness. Performance increases significantly as problem size increases which is opposite from the direction of influence on percent improvement in changeover time under these same conditions. The largest improvement in lateness occurs under large problem sizes and high coefficient of variations.

6.4 The effect of CV on performance

Percent improvement in changeover time against the initial MPS increases as CV increases regardless of the weight placed either criteria. High coefficient of variation of changeover matrices allows for a greater opportunity to search for an improved schedule. The largest improvement in changeover time always occurs under high coefficient of variations.

Percent improvement in lateness against the initial MPS increases as CV increases when equal weight is placed on both criteria or when 99% of weight is placed on lateness.
Under conditions where 99% of weight is placed on reducing changeover time there is no improvement in lateness against the initial MPS.

6.5 The Relative operating performance of scheduling heuristics

The relative performance of the scheduling heuristics is dependent on both the weight placed on the tradeoff parameter and the levels of the operating conditions. When a decision maker places 99% of weight on reducing changeover time, 3-OPT and Simulated Annealing outperform the Construction heuristic under small problem size with respect to percent improvement in changeover time against the initial Master Production Schedule. However, as problem size increases the Construction heuristic statistically outperforms both 3-OPT and SA, even though all three heuristics reduce a significant amount of changeover time relative to the initial MPS. This superior performance of the Construction heuristic relative to 3-OPT and SA under large problem sizes is due to its ability to batch all like products together as the schedule is being built. None of the heuristics are able to reduce lateness against the initial MPS under conditions where 99% of weight is on reducing changeover time.

The results also indicate that the Construction heuristic is not affected by changes in the levels of CV. However, the Construction heuristic is affected by changes in the levels of problem size. Performance against the initial MPS actually increases significantly as problem size increases.
When the weight is equally distributed between changeover time and lateness the changeover time and lateness performance against the initial MPS for 3-OPT and SA is significantly different than the Construction heuristic. As CV increases both 3-OPT and SA are able to reduce more changeover time and lateness time against the initial MPS whereas the Construction heuristics is not able to improve performance against the initial MPS. Therefore we can conclude that under operating conditions where a decision maker places equal weight on both criteria or 99% of weight on reducing lateness both 3-OPT and SA significantly reduce more changeover time and lateness time against the initial MPS than the Construction heuristic.

6.6 Influence of operating conditions on performance tradeoffs

It is apparent from the discussion above that operating conditions effect the relative performance of lateness and changeover time. In conducting this research we have identified a framework for identifying under what operating conditions tradeoffs occur between changeover time and lateness, and under what operating conditions does simultaneous improvement in performance occur. Figure 6.1 represents a framework to assist in understanding performance expectations when scheduling in process industries under operating conditions outlined in this dissertation. Though the performance measurements in this dissertation are changeover time and lateness other measurements such as earliness and tardiness could be substituted for lateness. This could lead to different results in Figure 6.1.
Simultaneous improvement in changeover time and lateness occurs under conditions when a decision maker places either equal weight on both criteria or 99% of weight on reducing lateness and the coefficient of variation level is high. With 99% of weight placed on reducing changeover time there were no environments where there was simultaneous improvement in both changeover time and lateness.

Tradeoffs between changeover time and lateness occurs under conditions when a decision maker places 99% of weight on reducing changeover time. Tradeoffs also occurs when a decision maker places equal weight on both criteria or 99% of weight on reducing lateness. Though this occurs only under conditions of large problem sizes and small coefficient of variations of changeover matrices. There also exists environments where heuristics provide no improvement against the initial MPS. This occurs mainly under small problem size conditions.

6.7 Suggestions for implementation

Before undertaking a full-scale attempt at implementing any scheduling heuristics, it was recommended that the production manager conduct a pilot study to: Calculate the coefficient of variation of changeover times and determine the number of orders in the Master Production Schedule. From this information a manager will be able to evaluate the firms position relative to Figure 6.1, thus helping to manage performance expectations.
6.8 Limitations and suggestions for future research

Of the many possible extensions to the research reported in this dissertation, the following are suggested as studies which could produce the most interesting and important results for both researchers and practicing managers.

1. Investigate the problem studied in this dissertation under a rolling planning horizon. This study could contribute to a better understanding not only of the effect of operating conditions upon performance of the scheduling heuristics, but also to previous literature on planning horizon length and updating frequency of the MPS.

2. Test the heuristics suggested in this dissertation under uncertainty in the MPS. Previous research on lotsizing has shown that uncertainty in demand leads to insignificant difference between lotsizing rules.

3. Perform a field study to collect data on actual changeover times. There is no field research reported in the literature on changeover time matrixes. The coefficient of variation of changeover times was proven to be a major factor in this dissertation. This study would focus on finding empirical data that would provide a better understanding as to exactly where plants are in reference to their coefficient of variation of changeover times.

4. Investigate the problem studied in this dissertation under a multi-stage production process. Previous research in the area multi-stage scheduling with sequence dependent changeovers has focused on exact solution techniques. These techniques have not been tested under the operating conditions presented in this dissertation i.e. coefficient of variation of changeover times and large problem sizes.

Since this dissertation represents the first experimental investigation devoted exclusively to studying single stage bi-criteria Master Production scheduling with sequence dependent changeovers, the suggestions provided above represent a few of the many studies that need to be conducted in order to identify and understand all of the
aspects of this problem. Pursuit of these or any other studies of the single stage bi criteria Master Production scheduling with sequence dependent changeovers problem, as well as any comments or suggestions regarding this study, are welcomed and encouraged by the author.

It is apparent that this research represents an exploratory investigation of single stage bi-criteria Master Production scheduling with sequence dependent changeovers in a single stage make-to-stock environment. To the extent the assumptions are restrictive, the results of this research are limited to understanding the basic trade-off involved and to focus attention on the nature of performance relationships. It is well known that simulation experiments do not explain the results of an experiment, yet simulation experiments do provide important insights into the problem area. Thus, it is anticipated that these results will provide sufficient insights and direction for further research.
<table>
<thead>
<tr>
<th></th>
<th>Wc/o</th>
<th>Wequal</th>
<th>Wlate</th>
</tr>
</thead>
<tbody>
<tr>
<td>high cv/ large size</td>
<td>Tradeoff</td>
<td>Simultaneous</td>
<td>Simultaneous</td>
</tr>
<tr>
<td>low cv/ large size</td>
<td>Tradeoff</td>
<td>Tradeoff</td>
<td>Tradeoff</td>
</tr>
<tr>
<td>high cv/ small size</td>
<td>Indistinguishable</td>
<td>Simultaneous</td>
<td>Simultaneous</td>
</tr>
<tr>
<td>low cv/ small size</td>
<td>Tradeoff</td>
<td>Indistinguishable</td>
<td>Indistinguishable</td>
</tr>
</tbody>
</table>

Note: Simultaneous indicates improvement in both criteria and indistinguishable indicates no significant difference between scheduling heuristics and MPS.

Table 6.1 Framework for Performance Tradeoffs (changeover time vs. lateness) for Bi-Criteria MPS in Process Industries.
APPENDIX A

3-OPT SCHEDULING HEURISTIC

c this is a 3-opt routine for a mps problem

c This routine uses a global swap.

INTEGER TABLE(10,10),dd_comp(10),TABLES(10,10)
inieger I,J,k,sch_length,mps_sequence_best(10)
integer MPS_sequence(10),due_date(10),best_sequence(10)
integer comp_date(10), run_time(26), r, s,t
real james
Integer due_date_new(10),sum_mps,sch_length_mps,b,c

p=.999
q = 1-p
open (unit = 1, file = 'james', status = 'old')

c data set 30
DATA (MPS_SEQUENCE(I), I = 1,10)
+/1,5,6,4,7,9,2,10,6,1/
DATA (DUE_DATE(I), I = 1,10)
+/6,29,41,47,53,53,76,88,100,106/

n=10

C CREATE CHANGEOVER MATRIX
DATA ((TABLE(I,J), J=1,10), I=1,10)
+/0,10,15,10,14,10,10,10,10,10,10,
+14,0,25,14,14,14,14,14,14,14,14,
+25,25,0,25,25,25,25,25,25,25,25,
+12,12,10,0,12,14,14,10,12,10,
+10,10,8,10,0,14,10,8,10,10,
+14,14,14,12,0,14,14,14,14,
+14,14,14,14,14,0,10,10,14,
+8,14,12,10,14,14,10,0,8,10,
+10,14,12,8,10,14,10,14,0,10,
+10,10,10,10,10,14,10,10,0/
best_sequence = mps_sequence
due_date_new = due_date

C TOTAL CHANGEOVER TIME FOR INITIAL MPS SEQUENCE
SCH_LENGTH_mps = 0
DO I = 1,n-1
SCH_LENGTH_mps = SCH_LENGTH_mps + (TABLE (MPS SEQUENCE(I),
+MPS SEQUENCE(I+1)))
c end if
END DO

C COMPLETION DATES FOR INITIAL MPS SEQUENCE
comp_date(1) = 0
do i = 2,n
COMP_DATE(i) = (TABLE (MPS SEQUENCE(i-1), MPS SEQUENCE(i)))
+ comp_date(i-1)
end do

C DIFFERENCE IN DUE DATE AND COMPLETION DATE IS
DO I = 1,n
DD_COMP(I) =ABS(DUE_DATE(I) - COMP_DATE(I))
END DO

C SUM OF THE DIFFERENCE OF COMPLETION DATE AND DUE DATE
SUM_mps = 0
DO 10 I = 1,n
SUM_mps = SUM_mps + DD_COMP(I)
10 CONTINUE

c calculate the objective function value
c we note that dividing each component of a vector by the norm
c of the vector normalizes a vector.

x = sch_length_mps/sch_length_mps
y = sum_mps/sum_mps
z = (p*x) + (q*y)

C print*,mps_sequence,x,y,z
write (1,34) 'mps', 'schedule','lateness','setup', 'time',
+ 'weighted','sum'
write (1,35) mps_sequence,y,x,z,sum_mps,sch_length_mps

c pause

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CALCULATING INITIAL SWAPS

200 continue
james = z

DO  I = 1,n-1
    do  j = i + 2, n + i - 3
        do  k = j + 2, n + i - 1

r = mod((i),n) + 1
s = mod((j-1),n) + 1
t = mod((K-1),n) + 1

u = r
v = s
w = t
trial = trial + 1

mps_temp = mps_sequence(u)
mps_sequence(u) = mps_sequence(w)
mps_sequence(w) = mps_sequence(v)
mps_sequence(v) = mps_temp

DUE DATE AND COMPLETION DATE FOR IMPROVED SEQUENCE

due_date_temp = due_date(u)
due_date(u) = due_date(w)
due_date(w) = due_date(v)
due_date(v) = due_date_temp

CALCULATE SCHEDULE LENGTH AND HEURISTIC LENGTH OF NEW SCHEDULE

SCH_LENGTH_old = 0
DO b = 1,n-1
SCH_LENGTH_old = SCH_LENGTH_old + (TABLE (MPS_SEQUENCE(b),
+ MPS_SEQUENCE(b+1))
END DO

comp_date(1) = 0
do d = 2,n
COMP_DATE(d) = (TABLE (MPS_SEQUENCE(d-1), MPSSEQUENCE(d))
+ + comp_date(d-1)
end do

sum of due date minus completion date
DO e = 1,n
DD_COMP(e) = ABS(DUE_DATE(e) - COMP_DATE(e))
END DO

SUM_old = 0
DO 80 f = 1,n
SUM_old = SUM_old + DD_COMP(f)
80 CONTINUE

x = (sch_length_old)/sch_length_mps
y = (sum_old)/sum_mps

zimprov = (p*x) + (q*y)

if (zimprov .lt. z) then
  z = zimprov
  l = u
  m = v
  o = w
else
  z = z
end if

mps_temp = mps_sequence(u)
mps_sequence(u) = mps_sequence(v)
mps_sequence(v) = mps_sequence(w)
mps_sequence(w) = mps_temp

due_date_temp =due_date(u)
due_date(u) = due_date(v)
due_date(v) = due_date(w)
due_date(w) = due_date_temp

write(1,35) mps_sequence
write(1,36) due_date

end do
end do
end do

if (z .ge. james) go to 40
mps_temp = mps_sequence(l)
mps_sequence(l) = mps_sequence(o)
mps_sequence(o) = mps_sequence(m)
mps_sequence(m) = mps_temp

due_date_temp = due_date(l)
due_date(l) = due_date(o)
due_date(o) = due_date(m)
due_date(m) = due_date_temp

go to 200

continue

C CALCULATE SCHEDULE LENGTH AND HEURISTIC LENGTH OF NEW SCHEDULE
SCH_LENGTH_old = 0
DO I = 1,n-1
   SCH_LENGTH_old = SCH_LENGTH_old + (TABLE (MPS_SEQUENCE(I),
   + MPS_SEQUENCE(I+1)))
END DO

comp_date(1) = 0
do d = 2,n
   COMP_DATE(d) = (TABLE (MPS_SEQUENCE(d-1), MPS_SEQUENCE(d)))
   + comp_date(d-1)
end do

c sum of due date minus completion date
DO e = 1,n
   DD_COMP(e) = ABS(DUE_DATE(e) - COMP_DATE(e))
END DO

SUM_old = 0
DO 180 f = 1,n
   SUM_old = SUM_old + DD_COMP(f)
180 CONTINUE

x = (sch_length_old)/sch_length_mps
y = (sum_old)/sum_mps

z = (p*x) + (q*y)

b = sum_old
c = sch_length_old

write (1,36)'best','schedule','lateness','setup','time',
+ 'weighted','sum'
write (1,35) mps_sequence,y,x,z,b,c
write (1,35) due_date

34 format (8x,a3,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)
35 format (i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,
+ 2x,f7.2,11x,f7.2,11x,f7.2,4x,i3,4x,i4)
36 format (7x,a4,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)

END
APPENDIX B

CONSTRUCTION SCHEDULING HEURISTIC

c Hill's construction heuristic

INTEGER TABLE(10,10), TABLES(5,5)
integer I,J,sl(10),r,due_date_new(10)
integer S(i0), D(10),d_n(10)
integer comp_date(10), K, s_n(10)
integer d_c(10),z(10),X,w,best_sequence(10)
integer dd_comp(10),run_time(26),g(10)

program limits
counter = 1
p= .999
q = 1-p

open (unit = 1, file = 'james', status = 'old')

set input data (due dates, initial schedule, and run time)

data set 30
DATA (S(I), I = 1,10)
+/1,5,6,4,7,9,2,10,6,1/
DATA (D(I), I = 1,10)
+/6,29,41,47,53,53,76,88,100,106/

n=10

c copy due date file from d array to g array
  g = d
  d_n(1) = d(1)

c initialize the beginning of the new schedule
  s_n(1) = s(1)

c set schedule length of first order
  e = 5
C CREATE CHANGEOVER MATRIX

DATA ((TABLE(I,J), J=1,10), I=1,10)
+ /0,10,15,10,10,14,10,10,10,10,
+ 14,0,25,14,14,14,14,14,14,14,
+ 25,25,0,25,25,25,25,25,25,25,
+ 12,12,10,0,12,14,14,10,12,10,
+ 10,10,8,10,0,14,10,8,10,10,
+ 14,14,14,14,12,0,14,14,14,14,
+ 14,14,14,14,14,0,10,10,14,14,
+ 8,14,12,10,14,14,10,0,8,10,
+ 10,14,12,8,10,14,10,14,0,10,
+ 10,10,10,10,10,14,10,10,10,0/

best_sequence = s
due_date_new = d

C TOTAL CHANGEOVER TIME FOR INITIAL MPS SEQUENCE
SCH_LENGTH_MPS = 0
DO I = 1,n-1
SCH_LENGTH_MPS = SCH_LENGTH_MPS + (TABLE (s(I),
+ s(I+1)))))
C end if
END DO

C COMPLETION DATES FOR INITIAL MPS SEQUENCE
comp_date(1) = 0
do i = 2,n
COMP_DATE(i) = (TABLE (S(i-1), S(i))
+ + comp_date(i-1)
end do

C DIFFERENCE IN DUE DATE AND COMPLETION DATE IS
DO i = 1,n
DD_COMP(I) =ABS(D(I) - COMP_DATE(I))
END DO

C SUM OF THE DIFFERENCE OF COMPLETION DATE AND DUE DATE
SUM_MPS = 0
DO 10 I = 1,n
SUM_MPS = SUM_MPS + DD_COMP(I)
10 CONTINUE
calculate the objective function value for initial schedule
C

\[
\text{normal} = \text{ABS}(\text{sch} \_\text{length}) + \text{ABS}(\text{sum})
\]

\[
\text{v} = (\text{sch} \_\text{length} \_\text{MPS})/\text{SCH} \_\text{LENGTH} \_\text{MPS}
\]

\[
\text{y} = (\text{sum} \_\text{MPS})/\text{SUM} \_\text{MPS}
\]

\[
\text{total} = (p \times v) + (q \times y)
\]

write (1,34) 'mps', 'schedule', 'lateness', 'setup', 'time',
+
'weighted', 'sum'
write (1,35) s,y,v,total

c

pause

C

SET PARAMETERS FOR CONSTRUCTION HEURISTIC

c b is counter for if then statement for updating due dates

c r is counter for construction heuristic.

c z is array for objective function value

c w is value to to find best z

c e is used to update the new due dates by subtracting setup time

c from previous order of construction heuristic

b=2

\[
Z(1) = 1000000
\]

c

start construction heuristic and set objective function value

c high so we know we will improve. do while loop is initialization and stopping

c rule. we want to stop when we have scheduled all n orders.

d o r = 1,n-1

w = 1000000

d o i = 2, n

c calculate the setup time for all products in array and choose

c for the next product that which has the smallest objective function value

\[
\text{sl}(i) = (\text{table}(s \_n(r), s(i)))
\]

\[
\text{D} \_\text{C}(i) = \text{ABS}(\text{D}(i) - \text{sl}(i))
\]

\[
\text{z}(i) = (p \times \text{sl}(i)) + (q \times \text{d} \_\text{c}(i))
\]

c

if then statement checks to see if the objective function value is less

c than the best. if so keep this order if not choose another.
if (z(i) .lt. w) then
  w = z(i)
  k = s(i)
  x = i
  s_n(b) = s(x)
else
  w = w
  s_n(b) = s_n(b)
end if
end do

c update parameters of due date array
  d_n(b) = g(x)
  d(x) = 5000000
  e = s_l(x)
  b = b + 1

do i = 1, n
  if (i .eq. 1) then
    d(i) = d(i)
  else
    d(i) = d(i) - e
  end if
end do
c performance measures

SCH_LENGTH_NEW = 0
DO I = 1, n-1
  SCH_LENGTH_NEW = SCH_LENGTH_NEW + (TABLE (s_n(I),
  + s_N(I+1))))
END DO
c
C COMPLETION DATES FOR INITIAL MPS SEQUENCE
comp_date(1) = 0
do i = 2, n
  COMP_DATE(i) = (TABLE (S_n(i-1), S_n(i))) + comp_date(i-1)
end do
C DIFFERENCE IN DUE DATE AND COMPLETION DATE IS
DO I = 1,n
DD_COMP(I) = ABS(D_n(I) - COMP_DATE(I))
END DO

C SUM OF THE DIFFERENCE OF COMPLETION DATE AND DUE DATE
SUM_NEW = 0
DO 20 I = 1,n
SUM_NEW = SUM_NEW + DD_COMP(I)
20 CONTINUE

v = (sch_length_NEW)/SCH_LENGTH_MPS
y = (sum_NEW)/SUM_MPS

total = (p*v) + (q*y)

write (1,36)'best','schedule','lateness','setup', 'time',
+ 'weighted', 'sum'
write (1,35) s_n,y,v,total

34 format (8x,a3,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)
35 format (i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,
+2x,f7.2,11x,f7.2,11x,f7.2)
36 format (7x,a4,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)

end
APPENDIX C

SIMULATED ANNEALING

c this program is a simulated annealing program to solve the
sequence dependent master production scheduling problem
INTEGER TABLE(10,10),I,J, TABLES(5,5)
integer MPS_sequence(10),due_date(10),best_sequence(10)
icntger comp_date(10), K, run_time(26), due_date_new(10)
icntger dd_comp(10),a,b,c,d,e,g,r,seed,seed
real james,w,v,x,y

p = 0
q = 1-p
Tmax = 1000000

ORDER_COUNTER = 0

open (unit = 1, file = 'james', status = 'old')

c data set 30
DATA (MPS_SEQUENCE(I), I = 1,10)
+/1,2,8,3,5,9,10,6,7,3/
DATA (DUE_DATE(I), I = 1,10)
+/7,20,27,34,34,47,47,75,108,115/

n=10

C CREATE CHANGEOVER MATRIX
DATA ((TABLE(I,J), J=1,10), I=1,10)
+ /0,4,44,4,4,38,4,4,6,6,
+ 28,0,58,4,4,30,6,4,8,4,
+ 60,60,0,60,60,60,60,60,60,
+ 6,4,4,0,6,8,6,4,8,6,
+ 6,6,4,4,0,8,6,4,6,6,
+ 8,6,4,8,8,0,8,6,8,10,
+ 8,6,8,10,10,6,0,4,6,8,
+ 4,8,6,6,10,6,6,0,4,4,
+ 6,10,6,4,6,10,6,10,0,6,
+ 6,6,6,6,6,10,6,4,0/

C TOTAL CHANGEOVER TIME FOR INITIAL MPS SEQUENCE
SCH_LENGTH_MPS = 0
DO I = 1,n-1
SCH_LENGTH_MPS = SCH_LENGTH_MPS + (TABLE (MPS_SEQUENCE(I),
+ MPS_SEQUENCE(I+1)))
c end if
END DO

C COMPLETION DATES FOR INITIAL MPS SEQUENCE
comp_date(1) = 0
do i = 2,n
COMP_DATE(i) = (TABLE (MPS_SEQUENCE(i-1), MPS_SEQUENCE(i)))
+ + comp_date(i-1)
end do

C DIFFERENCE IN DUE DATE AND COMPLETION DATE IS
DO I = 1,n
DD_COMP(I) =ABS(DUE_DATE(I) - COMP_DATE(I))
END DO

C SUM OF THE DIFFERENCE OF COMPLETION DATE AND DUE DATE
SUM_MPS = 0
DO 10 I = 1,n
SUM_MPS = SUM_MPS + DD_COMP(I)
10 CONTINUE

C normal = ABS(sch_length_old) + ABS(sum_old)
x = (sch_length_MPS)/SCH_LENGTH_MPS
y = (sum_mps)/sum_mps
z = (p*x) + (q*y)
james = z

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write (1,34) 'mps', 'schedule','lateness','setup', 'time',
+ 'weighted','sum'
write (1,35) mps_sequence,y,x,z

C CALCULATING INITIAL SWAPS
c counter = 0
100 continue
    jamez = z
c if (counter .eq. 240) go to 40
    DO 15 I = 1,n-1

    mps_temp = mps_sequence(i)
    mps_sequence(i) = mps_sequence(i+1)
    mps_sequence(i+1) = mps_temp

    due_date_temp = due_date(i)
    due_date(i) = due_date(i+1)
    due_date(i+1) = due_date_temp

    c calculate completion dates for mps schedule
    comp_date(1) = 0
    do c = 2,n
        COMP_DATE(c) = (TABLE (MPS_SEQUENCE(c-1), MPS_SEQUENCE(c)))
        + comp_date(c-1)
    end do

c sum of due date minus completion date
    DO d = 1,n
    DD_COMP(d) =ABS(DUE_DATE(d) - COMP_DATE(c))
    END DO

c calculate lateness measure
    SUM_new = 0
    DO 80 e = 1,n
    SUM_new = SUM_new + DD_COMP(e)
    80 CONTINUE

C CALCULATE SCHEDULE LENGTH OF NEW SCHEDULE
SCH_LENGTH_new = 0
    DO f = 1,n-1
       SCH_LENGTH_new = SCH_LENGTH_new + (TABLE (MPS_SEQUENCE(f),
               + MPS_SEQUENCE(f+1)))
    end if
END DO

calculate the objective function value

c normal = ABS(sch_length_new) + ABS(sum_new)
x = (sch_length_new)/sch_length_mps
y = (sum_new)/sum_mps

zimprov = (p*x) + (q*y)

if (zimprov .lt. z) then
  z=zimprov
  k=i

  mps_temp = mps_sequence(i)
  mps_sequence(i) = mps_sequence(i+1)
  mps_sequence(i+1) = mps_temp

  due_date_temp =due_date(i)
  due_date(i) = due_date(i+1)
  due_date(i+1) = due_date_temp

else
  z = z
  mps_temp = mps_sequence(i)
  mps_sequence(i) = mps_sequence(i+1)
  mps_sequence(i+1) = mps_temp

  due_date_temp =due_date(i)
  due_date(i) = due_date(i+1)
  due_date(i+1) = due_date_temp

endif

continue

c counter = counter + 1

if (z .ge. james) go to 40

  mps_temp = mps_sequence(k)
  mps_sequence(k) = mps_sequence(k+1)
  mps_sequence(k+1) = mps_temp
  due_date_temp = due_date(k)
  due_date(k) = due_date(k+1)
  due_date(k+1) = due_date_temp
comp_date(1) = 0
   do i = 2, n
      COMP_DATE(i) = (TABLE (MPS_SEQUENCE(i-1), MPS_SEQUENCE(i)))
      + comp_date(i-1)
   end do
   
c   sum of due date minus completion date
   DO I = 1, n
      DD_COMP(I) = ABS(DUE_DATE(I) - COMP_DATE(I))
   END DO

   SUM_new = 0
   DO 800 I = 1, n
      SUM_new = SUM_new + DD_COMP(I)
   
800   CONTINUE

C   CALCULATE SCHEDULE LENGTH AND HEURISTIC LENGTH OF NEW SCHEDULE
   SCH_LENGTH_new = 0
   DO I = 1, n-1
      SCH_LENGTH_new = SCH_LENGTH_new + (TABLE (MPS_SEQUENCE(I),
      + MPS_SEQUENCE(I+1)))
   end if
   END DO

   x = (sch_length_new)/sch_length_mps
   y = (sum_new)/sum_mps

   zimprov = (p*x) + (q*y)

   z=zimprov

   go to 100

40   continue

C   pause
C   Start of simulated annealing algorithm
C   set tmax the initial temperature: note this controls for the
C   number of iterations to be carried out
C   Tmax = 1000000
C   set the final temperature value tfinal: this in essence is the
C   stopping rule for which we terminate the scheduling routine
Tfinal = .05
set the temperature decay rate: controls for the number of
iterations to be carried out. The smaller the decay rate the
more iterations
drate = .90

mps_sequence = mps_sequence

random generator program
integer seed
iseed = 45001
seed = 45007
b = 11
a = 1
g = b - a

do while (Tmax .gt. Tfinal)
do i = 1,n
20 w = ran(iseed)
d = a + g*w
v = ran(seed)

iseed = iseed + 100
seed = seed + 100

start loop for random swap of orders
if (d .eq. i) go to 20
mps_temp = mps_sequence(i)
mps_sequence(i) = mps_sequence(d)
mps_sequence(d) = mps_temp

due_date_temp = due_date(i)
due_date(i) = due_date(d)
due_date(d) = due_date_temp

calculate completion dates for mps schedule
comp_date(1) = 0
do c = 2,n
COMP_DATE(c) = (TABLE (MPS_SEQUENCE(c-1), MPS_SEQUENCE(c)))
+ + comp_date(c-1)
end do

sum of due date minus completion date
DO h = 1,n
DD_COMP(h) = ABS(DUE_DATE(h) - COMP_DATE(h))
END DO

C calculate lateness measure
SUM_new = 0
DO 30 e = 1,n
SUM_new = SUM_new + DD_COMP(e)
30 CONTINUE

C CALCULATE SCHEDULE LENGTH OF NEW SCHEDULE
SCH_LENGTH_new = 0
DO f = 1,n-1
SCH_LENGTH_new = SCH_LENGTH_new + (TABLE (MPS_SEQUENCE(f), + MPS_SEQUENCE(f+1))
END DO

C calculate the objective function value
normal = ABS(sch_length_mps) + ABS(sum_mps)
x = (sch_length_new)/sch_length_mps
y = (sum_new)/sum_mps

zimprov = (p*x) + (q*y)
act = exp((-zimprov)/(Tmax/normal))

if (zimprov .lt. z) then
z = zimprov
else
if (v .lt. act) then
z = zimprov
else
z = z

mps_temp = mps_sequence(i)
mps_sequence(i) = mps_sequence(d)
mps_sequence(d) = mps_temp
due_date_temp = due_date(i)
due_date(i) = due_date(d)
due_date(d) = due_date_temp
endif
endif
end do

comp_date(1) = 0
do i = 2, n
   COMP_DATE(i) = (TABLE (MPS_SEQUENCE(i-1), MPS_SEQUENCE(i)))
   + comp_date(i-1)
end do

sum of due date minus completion date
DO 1 = 1, n
DD_COMP(I) = ABS(DUE_DATE(I) - COMP_DATE(I))
END DO

SUM_new = 0
DO 600 I = 1, n
   SUM_new = SUM_new + DD_COMP(I)
600   CONTINUE

C   CALCULATE SCHEDULE LENGTH AND HEURISTIC LENGTH OF NEW SCHEDULE
SCH_LENGTH_new = 0
DO I = 1, n-1
   SCH_LENGTH_new = SCH_LENGTH_new + (TABLE (MPS_SEQUENCE(I),
   + MPS_SEQUENCE(I+1)))
C   end if
END DO

x = (sch_length_new)/sch_length_mps
y = (sum_new)/sum_mps

z=improvement = (p*x) + (q*y)

Tmaxn =Tmax*drate
Tmax = Tmaxn
end do

C   best_sequence = mps_sequence

write (1,36)'best','schedule','lateness','setup','time',
+ 'weighted','sum'
write (1,35) mps_sequence,y,x,z

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c  print*, mps_sequence, x, y, z

34  format (8x,a3,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)
35  format (i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2,1x,i2, + 6x,f7.2,8x,f7.2,11x,f7.2)
36  format (7x,a4,1x,a8,15x,a8,6x,a5,1x,a4,6x,a8,1x,a3)

END
LIST OF REFERENCES


