## BORANG PENGESAHAN

 LAPORAN AKHIR PENYELIDIKANTAJUK PROJEK :
DYNAMIC SCHEDULING IN A MULTI-PRODUCT
MANUFACTURING SYSTEM

Saya: ASSOC. PROF. DR. ADNAN HASSAN
Mengaku membenarkan Laporan Akhir Penyelidikan ini disimpan di Perpustakaan Universiti
Teknologi Malaysia dengan syarat-syarat kegunaan seperti berikut :

1. Laporan Akhir Penyelidikan ini adalah hakmilik Universiti Teknologi Malaysia.
2. Perpustakaan Universiti Teknologi Malaysia dibenarkan membuat salinan untuk tujuan rujukan sahaja.
3. Perpustakaan dibenarkan membuat penjualan salinan Laporan Akhir Penyelidikan ini bagi kategori TIDAK TERHAD.
4.     * Sila tandakan ( / )


TANDATANGAN KETUA PENYELIDIK

Assoc. Prof. Dr. Adnan Hassan
Nama \& Cop Ketua Penyelidik
Tarikh : $\qquad$

CATATAN : * Jika Laporan Akhir Penyelidikan ini SULIT atau TERHAD, sila lampirkan surat daripada pibak berkuasa/ organisasi berkenaan dengan menyatakan sekali sebab dan tempob laporan ini perlu dikelaskan sebagai SULIT dan TERHAD.

# DYNAMIC SCHEDULING IN A MULTI-PRODUCT MANUFACTURING SYSTEM 

ASSOC. PROF. DR ADNAN HASSAN PROF. DR. AWALUDDIN MOHD SHAHAROUN MUCHAMAD OKTAVIANDRI

RESEARCH VOT NO. 75062

# DYNAMIC SCHEDULING IN A MULTI-PRODUCT MANUFACTURING SYSTEM 

## Assoc. Prof. Dr. Adnan Hassan

RESEARCH VOT NO. 75062

Dept. of Manufacturing and Industrial Engineering
Faculty of Mechanical Engineering
Universiti Teknologi Malaysia

# DYNAMIC SCHEDULING IN A MULTI-PRODUCT MANUFACTURING SYSTEM 

(Keywords: dynamic scheduling, job shop, ANN model, simulation scheduling)

To remain competitive in global marketplace, manufacturing companies need to improve their operational practices. One of the methods to increase competitiveness in manufacturing is by implementing proper scheduling system. This is important to enable job orders to be completed on time, minimize waiting time and maximize utilization of equipment and machineries. The dynamics of real manufacturing system are very complex in nature. Schedules developed based on deterministic algorithms are unable to effectively deal with uncertainties in demand and capacity. Significant differences can be found between planned schedules and actual schedule implementation. This study attempted to develop a scheduling system that is able to react quickly and reliably for accommodating changes in product demand and manufacturing capacity. A case study, 6 by 6 job shop scheduling problem was adapted with uncertainty elements added to the data sets. A simulation model was designed and implemented using ARENA simulation package to generate various job shop scheduling scenarios. Their performances were evaluated using scheduling rules, namely, first-in-first-out (FIFO), earliest due date (EDD), and shortest processing time (SPT). An artificial neural network (ANN) model was developed and trained using various scheduling scenarios generated by ARENA simulation. The experimental results suggest that the ANN scheduling model can provided moderately reliable prediction results for limited scenarios when predicting the number completed jobs, maximum flowtime, average machine utilization, and average length of queue. This study has provided better understanding on the effects of changes in demand and capacity on the job shop schedules. Areas for further study includes: (i) Fine tune the proposed ANN scheduling model (ii) Consider more variety of job shop environment (iii) Incorporate an expert system for interpretation of results. The theoretical framework proposed in this study can be used as a basis for further investigation.

## Key Researchers:

Assoc. Prof. Dr. Adnan Hassan<br>Prof. Dr. Awaluddin Mohd Shaharoun<br>Muchamad Oktaviandri

E-mail : Adnan@fkm.utm.my
Tel. No. : 07-5534850
Vote No.: 75062

## TABLE OF CONTENTS

## CHAPTER TITLE

ABSTRACT ..... ii
TABLE OF CONTENTS ..... iii
LIST OF TABLES ..... vi
LIST OF FIGURES ..... viii
LIST OF APPENDICES ..... ix
CHAPTER 1 INTRODUCTION
1.1 Background of the Problem ..... 1
1.2 Statement of the Problem ..... 3
1.3 Objectives of the Study ..... 4
$1.4 \quad$ Scope of the Study ..... 4
1.5 Importance of the Study ..... 4
1.6 Organization of the Report ..... 5
CHAPTER 2 LITERATURE REVIEW
$2.1 \quad$ Scheduling ..... 6
2.1.1. Introduction ..... 6
2.1.2. Notation for Scheduling ..... 9
2.1.3. Scheduling Classification ..... 11
2.1.4. Scheduling Complexity ..... 16
2.1.5 Scheduling Rules ..... 19
2.1.6 Performance Measures ..... 20
2.2. Job Shop Scheduling ..... 22
2.3. Dynamic Scheduling ..... 24
2.3.1. The Dynamic Job shop Scheduling Characteristics ..... 25
2.3.2 Previous Research on Dynamic Scheduling ..... 26
2.3.3 Dynamic Scheduling Approaches ..... 29
2.4 Simulation In Scheduling ..... 31
2.4.1 Motivation for Simulation ..... 33
2.4.2 The Steps of Simulation ..... 34
2.4.3 Scheduling Through Simulation ..... 37
2.5 Design of Simulation Experimentation ..... 37
2.5.1 Order Arrivals ..... 38
2.5.2 Processing and Setup Times ..... 40
2.5.3 Number of Machines ..... 41
2.5.4 Job Routing ..... 42
2.5.5 Machine and Shop Utilization ..... 43
2.5.6 Due Date ..... 43
2.5.7 Priority Rules ..... 44
2.6 Simulation and Its Application on Scheduling ..... 46
2.5 ANN for Solving Scheduling Problems ..... 48
2.5 Summary of Chapter 2 ..... 50
CHAPTER 3 RESEARCH METHODOLOGY
3.1 Traditional and Proposed Framework ..... 52
3.2 Operational Framework ..... 54
3.3 Research Questions ..... 55
3.4 Development Phases ..... 56
CHAPTER 4 MODEL DEVELOPMENT
4.1 Problem Definition and Training Samples Generation ..... 57
4-2 Simulation Model ..... 59
4.2.1 Steady-state Condition of the Shop (Warm up period) ..... 59
4.2.2 Run Length and Number of Replications ..... 60
4.3 ANN Model ..... 60
4.4 Sequences Codification Scheme ..... 62
CHAPTER 5 RESULTS AND DISCUSSION
5.1 Simulation Results ..... 63
5.2 ANN Training Results ..... 63
5.2.1 Parameter Used in the BP-MLP
5.2.2 The Training Convergent Curve
5-3 Comparison Between Simulation Results and Predict Results ..... 73
5.4 Discussions ..... 78
CHAPTER 6 CONCLUSSIONS ..... 83
REFFERENCES ..... 84
APPENDICES

## LIST OF TABLES

## Table 2.1 Description of Topics Covered by Reviews Articles in Scheduling.

Table 2.2 Classifies the Articles by Topics. 8
Table 2-3 Advantages and Disadvantages of Simulation 32
Table 2-4 Capabilities and Limitations of Simulation 32
Table 4-1 Original data of 6 X 6 job shop scheduling problem from 57 Fisher and Thompson (1963).

Table 5-1 Result from Simulation, Scheduling Rule = FIFO, Job Arrival = "Low"

Table 5-2 Result from Simulation, Scheduling Rule = EDD, Job Arrival = "Low"

Table 5-3 Result from Simulation, Scheduling Rule = SPT, Job Arrival $=$ "Low"

Table 5-4 Result from Simulation, Scheduling Rule = FIFO, Job Arrival = "Medium"

Table 5-5 Result from Simulation, Scheduling Rule = EDD, Job Arrival = "Medium"

Table 5-6 Result from Simulation, Scheduling Rule = SPT, Job Arrival = "Medium"

Table 5-7 Result from Simulation, Scheduling Rule = FIFO, Job Arrival = "High"

Table 5-8 Result from Simulation, Scheduling Rule = EDD, Job Arrival = "High"
Table 5-9 Result from Simulation, Scheduling Rule $=$ SPT, Job Arrival = "High"
Table 5-10 Training Parameters .73
Table 5-10 Training Parameters . ..... 73
Table 5.11 Comparison of Number Completed Jobs. ..... 74
Table 5.12 Comparison of Maximum Flowtime Job ..... 75
Table 5.13 Comparison of Average Machine Utilization ..... 76
Table 5.14 Comparison of Average Job Q Length for the Machine ..... 77

## LIST OF FIGURES

Figure 1-1: Summary Background of the problems. ..... 2
Figure 2-1, Models of Machine Configuration ..... 13
Figure 2.3, Flow Shops, Open Shops, and Job Shops. ..... 15
Figure 2-4, Simulation Modeling Processes ..... 34
Figure 3-1: Traditional Theoretical Framework ..... 53
Figure 3-2: Proposed Theoretical Framework ..... 54
Figure 3-3: Operational Framework ..... 55
Figure 3-4: Development Phases ..... 56
Figure 4-1: Physical configuration of a six-machine dynamic job shop. ..... 58
Figure 4-2, ANN Schedule Model ..... 61
Figure 4-3, Error Adjusted for ANN model. ..... 61
Figure 5-1: Mean Absolute Error Convergent curve of Training ..... 73
Figure 5.2 Comparison of Number Completed Jobs. ..... 79
Figure 5.3 Comparison of Maximum Flowtime Job ..... 80
Figure 5.4 Comparison of Average Machine Utilization ..... 81
Figure 5.5 Comparison of Average Job Q Length for the Machine ..... 82

## LIST OF APPENDICES

APPENDIX A: Most Common Scheduling Rules ..... 93
APPENDIX B: FIFO, SPT and EDD Algorithm ..... 94
Appendix C: Most Common Performance Measure ..... 97
APPENDIX D: Summary for Result from Simulation where Scheduling Rule ..... 98
= FIFO, Job Arrival = "Low"
APPENDIX E: Sequences Codification Scheme ..... 108

## CHAPTER 1

## INTRODUCTION

### 1.1 Background of the problem

The effect of globalization in every sector of the country, such as economic, information technology, communication, transportation, etc. has directly heightened customer expectation. Today's customers expect to be delighted with customized quality, lower price, time delivery, and service satisfaction. These situations have forced manufacturers to adapt changes in technology, among others, automated, flexibility and integrated system, rapid and short run manufacturing have been improved to respond customer expectation (Hassan, 2002). Figure 1.1 summarizes the background of the problems. Frequent changes due to the above mentioned factors have meant frequent rescheduling of production operation. Flexibility in reacting to changes in production scheduling has become an important attribute of modern manufacturing system.

One method of increasing the productivity of a manufacturing is by proper production scheduling of the jobs on the available machines/resources so that a high percentage of orders can be completed on time, average waiting time of orders minimized and utilization of the equipment maximized. The production schedulers (people who make scheduling) have to make a production schedule to meet shorten production lead time, to reduce work-in-process (WIP) inventory and to improve machine utilization. Even if he/she has special knowledge and experience for shop floor control, the scheduling job is much too complicated and time-consuming. To
solve these problems, schedulers have to use more effective and interactive production schedules.


Figure 1.1: Background of the problems.

There is always some degree of uncertainty present in the real manufacturing environment that can affect the reliability of any production schedule. When these dynamic events occur, the current schedule that uses some static assumption will no longer be considered optimal. Therefore, robust scheduling systems are desirable to be used in the manufacturing process.

The dynamics of real manufacturing system are very complex in nature. Schedule based on deterministic algorithms fail to deal with any disturbances, such
uncertainties as changes in demand and capacity. Significant differences can be found between planned schedules and actual process in progress. Based on this background, this study attempted to develop a production scheduling system that is able to react quickly, reliably, and can accommodate changes in demand and capacity.

### 1.2 Statement of the problem

Although most manufacturing scheduling problems are dynamic and stochastic in nature, the majority of available scheduling techniques are based on static and deterministic conditions. This is partly due to the difficulty in formulating and solving dynamic problems analytically. As a consequence, the solutions obtained from the traditional scheduling technique fail wherever changes occur to the system (Vieira, 2000).

Changes in manufacturing system can be defined as deviations which occur during production that cause such systems to behave differently from what is expected (Pendharkar, 1999). Changes can cause the scheduling system to perform its function either incorrectly or inefficiently. As a result, the changes can eventually prevent the system from accomplishing its objective or delivering products to customer on time. Changes in manufacturing can be classified into two broad categories (Vieira, 2000); (i) changes in demand, such as rush job, job cancellation by customer and changes in master production schedule, (ii) changes in capacity, such as unplanned machine breakdowns, illness of manpower and maintenance. Managing such changes is becoming critical in the era of time-based competition. For example, if a schedule is generated without considering possible orders in the future, new orders of significant urgency may interrupt those already scheduled, causing serious violation of their promised delivery dates. When this dynamic event occurs, the current schedule that uses some static assumption is no longer optimal.

### 1.3 Objectives of the Study

The research objectives are listed as below:
(i) To compare effectiveness of various scheduling rules in dynamic job shop scheduling.
(ii) To develop a decision support model for enabling analysis of dynamic scheduling of job shops under conditions of changing demand and/or capacity.

### 1.4 Scope of the study

The scope of research is limited to job shops, when jobs arrive in the shop in a dynamic and random manner to the scheduler.

- The study is limited to discrete products.
- Focusing on small and medium industries (SMI).
- The performance measures are limited to three: (i) minimization of the makespan, (ii) minimization of average tardiness and (iii) minimization of percentage number of tardy jobs


### 1.5 Importance of the study

The study is important and significant both from the theoretical and practical view point. The rationale and motivation for this study are:
(i). Traditionally, majority of current scheduling research assume static and deterministic condition, whereas, real manufacturing system are dynamic and stochastic in nature.
(ii). This study addresses small and medium sized industries, and aimed at non-specialist scheduler. Such people normally built a schedule from scratch to address a particular job, and then it is often discarded/
forgotten. This approach is very expensive, time consuming, and wasteful. There is a need for a schedule system that retains and builds on existing knowledge and be used as a predictive tool when unforeseen and dynamic changes occur to the manufacturing system

### 1.6 Organization of the Report

This report is organized into 6 chapters. Chapter 1 serve as an essential introduction to the research. Chapter 1 provides background information and a review of related literature that leads to the formulation of this report. Chapter 1 describes the research methodology and its rationale. Chapter 4 describes models development. Chapter 5 presents the data result and discussion. Chapter 5 provides an overall conclusion and suggestions for future research.

## CHAPTER 2

## LITERATURE REVIEW

### 2.1 Scheduling

### 2.1.1. Introduction

Scheduling deals with the allocation of scarce resources to task over time. It is a decision-making process with the goal of optimizing one or more objectives (Pinedo, 2002). Scheduling is important issue in management of organizations because it determines the cost and services reputation of the company with respect to the competition. The need to respond to market demand quickly and run plants efficiently raises complex scheduling problems in almost all but the simplest production environments.

The theory of scheduling has received significant attention since its beginning in the early 1950. A representative, although not complete, list of the most important survey on the field are: (Graves, 1981), ( Sen and Gupta, 1984) (Ramashes, 1990), (Sevastjanov, 1994), (Nagar, 1995), (Blazewick et al., 1996) (Hall, 1996), (Drexl, 1997), (Mokotoff, 2001) and (Raheja and Subramaniam, 2002), (Lee et. al, 1997) . Table 2.1 provides a brief summary of the topics covered by each article, while Table 2.2 classifies the articles by topics.

In additional, (Conway, et al., 1967), (Baker, 1974) ), (Rinooy Kan, 1979), (Gupta, 1981), (French, 1982), (Blazewicz, et al, 1993), (Brucker, 1995), (Jordan, 1996), ( Kimms, 1997), (Pinedo, 2002), and (Cottet, 2002) are book containing most of the basic theoretical knowledge accumulated to date. Partly under the influence of

Conway et al., (1967), the activities to be scheduled are represented by job and the resources by machine. Thus, the scheduling problem can be verbally formulated as the determination of the optimal order of operations and jobs on each machine center based on overall criterion of measurement. This ordering of jobs and operations is called a schedule and assign jobs and operation to machine center.

Table 2.1 Description of Topics Covered by Reviews Articles in Scheduling.

| Article | Scheduling Topics Covered |
| :--- | :--- |
| Graves, 1981 | Classification of scheduling in problem classes and review of <br> theoretical developments used to solve them. Discussion on the <br> discrepancy between theory and practice and suggestion of six <br> areas worth of further research. |
| Sen and Gupta, | Discussion of scheduling techniques with performance measures <br> related to due dates. A Classification based on scheduling <br> objectives and a review of theoretical development and <br> computational experiences is presented. |
| Ramashes, 1990 | Provides a state-of-the-art survey of simulation-based research <br> on dynamic job shop scheduling with a distinct emphasis on two <br> important aspect, i.e. first, scheduling approaches taken on job <br> shop simulation modeling and experimental, second focus on <br> research finding on the job shop performance criteria of interest. |
| Sevastjanov, | Survey on geometric method used in scheduling theory as <br> approximation algorithm. |
| 1994 | Provides a detailed literature survey of multiple and bicriteria <br> problems in scheduling. A broad classification scheme for <br> scheduling problems is also provided. |
| Nagar, 1995 |  |

Table 2.1 Continued.

| Article | Scheduling Topics Covered |
| :--- | :--- |
| Hall, 1996 | Review the computational complexity of a wide variety of no- <br> wait and blocking scheduling problems and describe several <br> problems which remain open as to complexity. |
| Drexl, 1997 | Summarizes recent work in the field of lot sizing and scheduling <br> to explain differences o formal models and to provide some first <br> readings recommendations. This paper also propose two <br> research direction i.e. continuous tie models and multi-level lot <br> sizing and scheduling. |
| Mokotoff, 2001 | Presented an overview of the research devoted to the parallel <br> machine with emphasis on the case of the optimal makespan on <br> identical parallel machine. |
| Raheja and <br> Subramaniam, <br> 2002 | Provides a comprehensive review of literature on the reactive <br> recovery of job shop schedules. This paper also proposes further <br> research work in job shop scheduling area. |
| Lee, et al., 1997 | Review some of the recent developments in the theory, the <br> heuristic search methods, and the practice of deterministic <br> scheduling. This paper also describes problem classification, <br> complexity and analytical approaches of deterministic <br> scheduling. |

Table 2.2 Classifcation the Articles by Topics.

| Topic | Related articles |
| :--- | :--- |
| Comprehensive and Historical <br> Surveys | (Blazewick et al., 1996), (Nagar 1995), <br> (Drexl, 1997), (Raheja and Subramaniam, <br> 2002) |
| Heuristic and Approximation <br> algorithms | (Sevastjanov, 1994) |

Table 2.2 Continued.

| Topic | Related articles |
| :--- | :--- |
| Complexity Theory and <br> Combinatorial Optimization | (Hall, 1996), (Lee, et al., 1997) |
| Analysis and Discussion of <br> Performance Measures | (Sen and Gupta, 1984), (Ramashes, 1990), <br> (Mokotoff, 2001) |
| Relation between Scheduling <br> Practice and Scheduling | (Graves, 1981) |

### 2.1.2. Notation for Scheduling

Using the classification scheme developed by Conway, et al., (1967) and the refinements introduced by McCharty and Liu, (1993) it is possible to denote a scheduling problem using four field notation $\mathrm{A} / \mathrm{B} / \mathrm{C} / \mathrm{D}$ where,

A- integer representing the number of jobs, N ;
B- integer that represent the number of machine center, M;
C- flow pattern and technological constraint. Values of C are;
$J, b_{m} \leq b^{*}$ job shop with $b_{m}$ machines per machine center $m$ bounded by an integer $\mathrm{b}^{*}$;

G: General job shop;
b-parallel: shop with b machines in parallel;
F: flow shop;
F-perm: permutation flow shop;
O: open shop;
| |: single machine shop.
In some case, the above symbols might be accompanied by the expression $\mathrm{n}_{\mathrm{i}} \leq \mathrm{n}^{*}$ denoting that the number of operations per job is bounded by an integer $\mathrm{n}^{*}$.

D- criteria to be optimized. E.g., $\mathrm{C}_{\text {max }}$.

While this four field notation is suitable for basic problems, when non-basic problems (involving pre-emption, dependent jobs, etc.) require classification the three field notation ( $\alpha|\beta| \gamma$ ) of Graham et al. (1979) is more appropriate (Pinedo, 2002):
$\alpha$ - machine environment (contain a single entry). The possible values for machine environments specified in the $\alpha$ field are:
(1) : Single machine
(Pm) : Identical machine in parallel
(Qm) : Machine in parallel with different speed
(Rm) : Unrelated machines in parallel
(Fm) : Flow Shop
(FFc) : Flexible flow shop
(Jm) : Job shop
(FJc) : Flexible job shop
(Om) : Open shop
$\beta$ - processing characteristic and constraint (may contain no entry at all or multiple entries). The possible entries in the $\beta$ field are :

| $\left(\mathrm{r}_{\mathrm{j}}\right)$ | $:$ Release date |
| :--- | :--- |
| $\left(\mathrm{s}_{\mathrm{j}}\right)$ | $:$ Sequences dependent setup times |
| $(\mathrm{prmp})$ | $:$ Preemption |
| (prec) | $:$ Precedence constraint |
| (brkdwn) | $:$ Breakdown |
| $\left(\mathrm{M}_{\mathrm{j}}\right)$ | $:$ Machine eligibility restriction |
| $($ prmu $)$ | $:$ Permutation |
| (block) | $:$ Blocking |
| (nwy) | $:$ No-wait |
| (recrc) | $:$ Recirculation |

$\gamma$ - objectives to be minimized (usually contains a single entry). Examples of possible objective function (in the $\gamma$ field) to be minimized are:

- Makespan ( $\mathrm{C}_{\max }$ )
- Maximum Lateness $\left(\mathrm{L}_{\max }\right)$
- Total weighted completion time $\left(\sum w_{j}\left(C_{j}\right)\right)$
- Discounted total weighted completion times $\left(\sum w_{j}\left(1-e^{-r C j}\right)\right)$
- Total weighted tardiness $\left(\sum w_{j} T_{j}\right)$
- Weighted number of tardy jobs $\left(\sum w_{j} U_{j}\right)$

MacCarthy and Liu (1993) indicate that the four field technique has been widely used and is familiar to most schedule researches. Consequently they propose a combination of the two methods where the C field is modified to take into account non-basic models.

### 2.1.3. Scheduling Classification

Scheduling problems can be classified in many ways, such as base on job arrival, information flow to the scheduler, production stages, resources configuration and flexibility of resources (Bongaerts, 1998, French, 1982).

## a. Based on Job Arrival

According to availability of jobs prior to the creation of the schedule, scheduling system can be classified as static and dynamic. In static scheduling all jobs are identified when creating the scheduling, and once the production sequences are defined, they are assumed not to be changes during processing. In dynamic scheduling, jobs arrive dynamically over time and are scheduled after arrival.

## b. Based on Information to the Scheduler

Base on information to the scheduler, scheduling system can be classified as Deterministic or stochastic. When processing times and all other parameter are known and fixed, we call our problems deterministic. Problems, which the processing times, etc. is uncertain, are called stochastic.

## c. Processing Complexity

Processing complexity refers to the number of processing steps and workstation associated with the production process. This dimension can be decomposed further as follows:

1. One stage, one machine,
2. One stages, multiple machine,
3. Multistage, flow shop,
4. Multistage, job shop.

## d. Based on Resources Configuration

Base on models of Machine arrangement, the following scheduling problems can be defined (Blazewick et al., 1994) as shown as Figure 2.1. Base on layout/configuration of the machines (Figure 2.1), the following scheduling problems can be defined:

Single machine model (French, 1982) has the simplest layout. It consists of a single machine that performs all operations. For models of machine in scheduling, the single machine model represents the simplest case. In a single machine problem,
one machine (acting independently) is considered to be the only limited resources. It is assumed that a single machine has a fixed capacity which allows one task to be processed at any instant (i.e., a batch processor is not termed a single machine)


Figure 2-1: Models of Machine Configuration

Other simplifying assumption are typically made in a single-machine problem, the most common being that the single machine processes at a constant rate and is available and fully functional at all times. This last assumption is not peculiar to single machine problems - it is an assumption made in the vast majority of scheduling problems.

The single machine is a one-machine one-resource problem, this being a special case of one-machine problems (Dunstall, 2001). One machine problems are those that deal with any production facility consisting of one processor acting independently and having a one-operation-at-a-time processing capacity.

A parallel machine problem is a special case of a multi-machine problem. A group of machines are commonly described as parallel machines if they serve a single input queue of waiting jobs (Figure 2.2). Typically, a parallel machine problem involves machine that individually are single machines.

There are three basic types of parallel machines modeled in scheduling problems: identical parallel machines, uniform or proportional parallel machines, and unrelated parallel machines. In a problem with identical parallel machines, all machine operate at the same speed (processing rate) and have the same processing capabilities. Uniform machines have the same processing capabilities but each has a different processing rate. $\rho_{\mathrm{m}}\left(\rho_{\mathrm{m}}>0,1 \leq \mathrm{m} \leq M\right.$ ), with the processing time of job j on machine $m$ given by processing rate $P_{m j}=P_{j} / \rho_{m}$ for a given processing requirement for $P_{j} j$ job $a_{j}$.


Figure 2.2: A Representation of Parallel Machine and a Single Input Queue.

Unrelated parallel machine represent the most complex of the three standards parallel machine type; such machine do not necessarily have identical processing capabilities, and the processing time of each job on machine $m$ need not be related to either the processing times of other jobs on the same machine or to the processing time required on other machines. For each job j and machine m, a "job-dependent speed" $P_{m j}$ is specified and used to provide processing time $P_{m j}=P_{j} / \rho_{m j}$. If a job cannot be processed on a certain machine, the use of value of $\rho_{\mathrm{mj}}$ "near to zero" can
prohibit the job from being scheduled on that machine, due to the extraordinarily large processing time assigned to it.

An interesting extension to the "standard" parallel machine model is the parallel multi-purpose machine models. Each job or operation of a job can be processed on a particular subset of the parallel machines, and the parallel machines are otherwise either identical or uniform. Only a small amount of scheduling research has been directed toward multi-purpose machine models, although interested readers are referred to (Brucker, 1995), for example.

Single and parallel machines can be seen as representing individual processing units, or workcenters, in a plant. Where the execution of entire workorders (i.e., all operation of a job) can be carried out on one workcenter, these machine models can incorporate almost all of the relevant machine characteristics.

The applicability of single or parallel machine models is limited. Other multimachine, multi operation models are required to appropriately model many facilities. There are three classical multi-machine models in addition to the parallel machine model that regularly appear in the scheduling literature, these being (Figure 2.3):


Figure 2.3: Flow Shops, Open Shops, and Job Shops.

- Flow shop, where all work flows from one machine (workcenter) to the next; that is job share a common operation (processing) order and hence a common routing through the shop. A flow shop model implies that chain precedence holds between the operations of each job. In simple word, flow shop is a model, where every job visits several machines, but all job have same sequence
- Job shop, where operations of a job must be carried out in prespecified order (chain precedence) and on a prespecified machine (or parallel machines), so that individual job routings are fixed, but can vary between jobs. In simple word job shop is a model, where every job visits several machines, but with dependent sequence and routing specified;
- Open Shops, Where restrictions are not placed on the operation order (no precedence). Job routings are part of the decision process, but operation-machine assignments are predetermined. In simple word, open shop is a model, where every job visits several machines, but with dependent sequence and routing not specified;

Some multi-machine environments will be inadequately represented within the classical classification scheme of flow shop, open shops, and job shops. For the purpose of this chapter, however, there is no need to extend the classification.

### 2.1.4. Scheduling Complexity

The theory of computational complexity can be traced back to the works of and (Karp, 1972) who first studied the relation between the classes $P$ and $N P$ of language recognition problems solvable by deterministic and non deterministic Turing machine respectively. This language recognition problem can be solved in a number of steps bounded by a polynomial function in the length of the input. With respect to combinatorial optimization, where deterministic scheduling problems belong, a rigorous mathematical definition of concepts is not needed (Lenstra, et. al. 1977), and it is sufficient to identify with $P$ the class problems for which a polynomial-bounded, good or efficient algorithm exist (Edmon, 1965). On the other hand, all problems in NP can be solved by polynomial-depth backtrack search.

In the original context of complexity theory, all problems are stated in term of recognition problems which require a yes/no answer. To deal with the complexity of a combinatorial minimization problem, a transformation into the problem of determining the existence of a solution with value at most equal to $z$, for some threshold value $z$, is needed.

Problems in $N P$ are not all equal in term of computational difficulty. It is clear that $P \subset N P$, but the proper inclusion is not yet known to be true or false. In fact one of the most intriguing open question is whether or not $P=N P$.

There are some problems of the $N P$ class, however, that are considering the most difficult ones.

This is the NP-complete class. To clearly define this class, one must first define a problem $P^{\prime}$ as being reducible to a problem $P$. denoted $P^{\prime} \propto P$, if for any instance of $P$ ' an instance of $P$ can be constructed in polynomial-bounded time such that solving the instance of $P$ will solve the instance of $P^{\prime}$ instance. $P$ is called $N P$ hard if $P^{\prime} \propto P \forall P^{\prime} \propto N P$, and $P$ is $N P$-complete if $P$ is $N P$-hard and $P \notin N P$ (Lenstra and Rinnooy Kan 1979). The theory of $N P$-completeness provides many straightforward techniques for proving that a given problem is "just as hard" as a large number of other "very difficult" problems. Thus, the theory of NPcompleteness assists designers of algorithms in directing their problem solving efforts toward those approaches that have the greatest likelihood of leading to useful algorithms (Garey and Johnson, 1979).

Establishing $N P$-completeness for a scheduling problem is a strong justification for the use of enumerative methods, since no better optimal algorithm is likely to exist. (Graham, et. al., 1979) have catalogued approximately 9.000 scheduling problems according to their computational complexity. Roughly 9\% of these are $P, 77 \%$ are $N P$-hard, and the remaining $14 \%$ are open. (Legeweg, et. al., 1981) describe a computer program that maintains a record of the known complexity results for a structured class of combinatorial problems. Given listing of well-solved and $N P$-hard problems, the program employs a reducibility relation defined on the class to classify each problems s easy, hard or open and to open one, the hardest open ones and the easiest hard ones. The program was applied to class of 4536 machine
problems. The result indicates that 416 (9\%) are $P, 3730$ ( $82 \%$ ) are $N P$-hard, and the remaining 390 (8\%) are still open (Lenstra and Rinnoy Kan 1984, 1985).

From a practical point of view, in order to solve $N P$-hard and $N P$-complete problems there is a need to:
(1) relax some of the constraints;
(2) use approximation algorithms and/or heuristics, and;
(3) use exact exponential algorithms.

Relaxation for scheduling problems is concerned with task preemptions, unit processing times, weaker precedence constraints, etc. The use of approximation algorithm requires an analysis of the quality of the solutions, where the distance to the optimum may be evaluated either in the worst case or on the average (Feisher, 1980). In the case of heuristic, a benchmark of problems might be used to suggest performance on practice with respect to parameters describing specific instances of the heuristic. Exact exponential algorithm are used mainly for small instances of the problem or for solving problems of special structure (blazewicz, et. al., 1988).

To further limit the complexity of the problem, the following assumptions are made for the models development below:

1. Each job, denoted by a work order, is an entity;
2. No pre-emption;
3. Each job has m distinct operations, one on each machine;
4. No cancellation;
5. The processing times are independent of the schedule;
6. In-process inventory is allowed;
7. There is only one of each type of machine;
8. Machine may be idle;
9. No machine may process more than one operation at time;
10. Machines never break down, and are available throughout the scheduling period;
11. The technological constraint are known in advance and are immutable;
12. There is no randomness, in particular:

- The number of jobs is known and fixed,
- The number of machines is known and fixed,
- The processing times are known and fixed,
- The ready times are known and fixed,
- All other quantities needed to define a particular problem are known and fixed.

There are standard assumption in job shop research ((Baker, 1974), (Conway, et. al., 1967), (Blazewicz, et. al. 1993)), and obey to historical reasons based on the need for simple models that can capture the essence of a scheduling problems very difficult to solve if all possible variables that influence it are considered ((Sisson, 1959), (Mellor, 1966), and (Gere 1966)). Even though these assumption have been challenged on the basis of generalization an lack of applicability to real scheduling problems, it is also true that for most practical problems it is sufficient to get good suboptimal solution and, therefore, theoretical work and development of heuristic on simple models is still needed (Kan, 1979)

### 2.1.5 Scheduling Rules

A scheduling rule is used to select a job to be processed from a set of jobs waiting for services (these rules can also be used to introduce workpieces into the system, to route the parts in the system and also to assign parts to facilities). Scheduling rules may be static or dynamic. Because of the large number of scheduling rules, it is not obvious which scheduling rule to select in a given environment. However, have shown that the selection of the scheduling rules can have a significant impact on system performance. Hence, in recent years, substantial research and study has been carried out in analyzing these scheduling rules (Table 3).

### 2.1.6 Performance Measures

A variety of performance measures guide rescheduling. These measures can be separated into three groups (Jain and Elmaraghy, 1997; Shafaei, and Brunn, 1999; Wu, Storer, and Chang, 1993): measures of schedule efficiency, measures of schedule stability, and cost.

Measures of schedule efficiency are often used when generating a production schedule. They are generally time-based measures (Shafaei and Brunn, 1999): makespan (Yamamoto, and Nof, 1985; Sabuncuoglu, and Karabuk, 1999; Fang, and Xi, 1997; Wu, Storer,and Chang, 1993), mean tardiness (Jain and Elmaraghy, 1997 Sabuncuoglu and Karabuk, 1999), mean flow-time (Jain and Elmaraghy, 1997), average resource utilization (Jain and Elmaraghy, 1997), and maximum lateness (Church and Uzsoy, 1992).

Schedule stability is not an issue in static, deterministic rescheduling environments since the schedule does not need updating. However, in other rescheduling environments, stability, nervousness, and robustness are important measures. Wu, Storer and Chang (1993), for instance, have said that the impact of schedule change is a non-regular performance measure defined in two ways: (1) the starting time deviations between the new schedule and the original schedule, and (2) a measure of the sequence difference between the two schedules. Abumaizar and Svestka (1997) proposed similar ideas saying that measures of stability deal with deviation from the initial schedule. Watatani and Fujii (1992) and Dhingra, Musser and Blankenship (1992) also considered the deviation between the revised and initial schedules as performance measures, even though they did not call it schedule stability.

The impact of machine failure seems to be the major concern when searching for more stable (less nervous) and robust schedules. Shafaei and Brunn (1999) have addressed the robustness of scheduling rules in a dynamic and stochastic environment. They concluded that as the level of uncertainty increases, frequent rescheduling becomes more effective in improving the robustness of the schedules. Wu, Storer, and Chang (1993) have studied rescheduling heuristics using schedule
efficiency (makespan) and schedule stability as performance measure criteria. For the single-machine system they have considered, the heuristic used generated stable schedules while retaining near-optimal makespans.

Time-based performance measures (measures to reach schedule efficiency) do not completely reflect the economic performance of the manufacturing system. So, due to the lack of an overall, efficient, time-based performance measure, researchers have recognized that the scheduling decisions should also be evaluated by using an economic performance measure. The objective then is to minimize the cost of starting jobs too early, work-in-process inventory, and tardiness. Issues such as job profitability, total cost minimization, reduction in WIP, and the cost of missed due dates are more important for managers than the time-based measures mentioned above (Shafaei and Brunn, 1999). Shafaei and Brunn (1999) have proposed the use of a total cost function in terms of job due date, completion time, number of jobs, number of operations, operation processing time, job raw material cost, processing cost of operations, job revenue, processing start times, job release time, job tardiness, holding cost rate, and tardiness cost rate.

In general, rescheduling costs occur in three categories: computational costs, setup costs, and transportation costs. Computational costs include the computational burden on the computer running the scheduling system (Sabuncuoglu and Karabuk, 1999; Church, and Uzsoy, 1992), the non-recurring costs of investments in the necessary information systems (sensors, displays, communication networks, hardware, and software), and the recurring costs of administration, maintenance, and upgrades. If rescheduling is done manually, then the computational cost includes the time that the planners, managers, and supervisors spend generating and updating schedules. Setup costs occur when tooling and fixtures are created or allocated in advance according to the schedule. Thus a change in the schedule will incur costs to reallocate pallets and replan the tools (Olumolade, and Norrie, 1996). Transportation costs (also called material handling costs) are related to delivering materials earlier than required or additional material handling work to transport jobs from one scheduled machine to other points in the shop (Olumolade and Norrie, 1996). For instance, Bean et al. (Bean et. al., (1991)) use the number of jobs reassigned as a measure of solution cost that must be balanced against tardiness costs and
computational effort. In dynamic rescheduling environments, the relative values of the rescheduling period and the mean total processing time requirements of a job will affect the performance measures used in predictive-reactive rescheduling. When the rescheduling period is relatively large, jobs can be started and completed between rescheduling events. Scheduling objectives will typically focus on completing the available jobs within that time period. When the rescheduling period is relatively small, the system will have, at each rescheduling point, some jobs that are available and waiting to start and many others that started during a previous period but still require more processing. In a job shop environment, scheduling objectives are much more complex, since there is a need to balance available capacity among jobs at different stages in their processing. This is especially true in shops with re-entrant flow, like those found in semiconductor wafer fabrication plants (Kumar, 1994; Kempf, 1994).

### 2.2. Job Shop Scheduling

A job shop is a process-based manufacturing system in which jobs for different orders follow different routing or sequences through processes and machine (Black, 1983). The major characteristic of this system are flexibility, variety, highly skilled workers, much direct labor and great deal of manual material handling.

A schedule for job shop is an allocation of one or more time interval on one or more machine to each job. Job shop is one of the scheduling problems that have been study extensively because of its similarities to real production system. In a job shop, a job may require several different operations performed by different machines, and it may have to wait in several different queues. If jobs arrive at the shop randomly over time, the job shop is called a dynamic job shop (Jackson, 1963).

The objective of job shop scheduling problem usually is to find a processing order or a scheduling rule on each machine for which a chosen measure of performance is optimized. Job shop scheduling problems are very difficult to solve.

The analytical approach has been proved to be extremely difficult to solve, even with several limiting assumption (Jackson, 1963)

Therefore, research on scheduling a job shop has focused primarily on identifying dispatching rules that perform well under a variety of shop condition or a variety of shop criteria (Philipoom, 1990). In job shop scheduling, a dispatching rules is a priority assignment algorithm that is used to assign priority to the jobs in queue and then decide which task from a set awaiting processing is to be perform next (Fry et al., 1988).

The great variation of dispatching rules reflects the amount of work in this area. In 1977, Panwalker and Iskander published a paper that categorized and listed 113 scheduling dispatching rules. In 1984, Sen and Gupta reviewed the static scheduling problem whose performance measures are related in some ways to job due dates. In 1990, Ramashes published survey paper on simulation-based research of job shop scheduling.

However, although a large number of dispatching rules have been studied, none of the claim to be the one that can operates effectively in all shop condition. In 1976, Weeks and Fryer found that the performance of some dispatching rules was influenced by the due date assignment method. In 1983, Elvers and Taube investigated the performance of five scheduling rules at six different shop-utilization levels and concluded that the relative performance of the rules was dependent on the shop-load level. In 1984, Baker verified the existence of crossover points, with some rules performing better for thigh due dates and other for loose ones. Also, in 1984. Kiran and Smith concluded that SPT is likely to perform better than slack per operation (S/OPN) in a shop that has high utilization and tight processing time independent due dates. There is no dispatching rule that has been shown to consistently produce better result than all other rules under a variety of shopconfiguration and operating condition.

### 2.3. Dynamic Scheduling

Scheduling algorithm themselves can be characterized as being either static or dynamic (Cheng et al., 1988). A static approach determines schedules of process in advance; it requires prior knowledge of a process's characteristics but requires little runtime overhead since a completed schedule is known before the operation is started. By comparison, a dynamic method determines schedules at runtime, thereby furnishing a more flexible system that can react to changes in activities beyond those that were anticipated.

In a manufacturing environment, change is an inevitable element of daily life; hence, frequent scheduling changes are necessary (Hoitomt and Luh, 1993). An important factor that affects the scheduling of jobs is the dynamic variation of factory status (Sarin and salgame, 1990), (Buxey, 1989) suggest a list of factors that usually occur in the production and may influence the value of any production schedule. These factors are:
a. An unpredictable level of absenteeism.
b. Equipment under breakdown/repair.
c. The volume of information to be handled allows requirements to be calculated at an aggregate level only.
d. Time spent queuing at process stages, and for transport between them, is highly variable.
e. Operation times used for planning purpose are rough estimates.
f. Customer (or the marketing department) may cancel orders on short notice or alter design specification, order quantity, delivery date, etc., even after work has commenced.
g. Following quality inspection, items may be scrapped, downgraded, or scheduled for reworking.
Thus far, it can see there is always some degree of uncertainty present in the factory environment that can destroy the credibility of any production schedule that is over-ambitious in its specification. When these dynamic events, the current schedule that uses some static assumption is no longer optimal (Yamamoto and Nof,
1985). Therefore, the desire for a flexible, integrative, and robust schedule system to be used in the manufacturing process is understandable.

### 2.3.1. The Dynamic Job Shop Scheduling Characteristics

The static job shop scheduling problem can be described as follows (Kuroda and Wang, 1996): Given M machines and J jobs, the J jobs are to be processed on the M machines. Each job consists of $P$ operations processed on the $M$ machines. A schedule is feasible if each job can only be processed on one machine and each machine can only process one job at a time. Some jobs have prescribed routing through the m machines, but the routing for each of these jobs may be different. The objective function is generally to minimize the maximum completion time (makespan), which is equivalent to minimizing cycle time.

Based on the definition of the Static Job Shop Scheduling problem, the dynamic job shop scheduling problem may be characterized as follows: in a manufacturing system which comprises $M$ machines (work stations) the jobs arrive continuously in time. Each job consists of a specified set of operations, which have to be performed in a specified sequence (routing) on the machines. Schedules for processing the jobs on each of the $M$ machines have to be found which are best solutions with respect to given objective(s) function or performance measure(s) . Because of the constrained information horizon (the arrival times, routings and processing times of the jobs arriving in future are not known in advance) only for those jobs currently in the shop processing sequences on the various machines can be determined. The decision as to which job is to be loaded on a machine, when the machine becomes free, is normally made with the help of a dispatching (scheduling) rule.

### 2.3.2 Previous Research on Dynamic Scheduling

Dynamic scheduling is closely related to real-time control, since decisions are made based on the current state of the manufacturing system. Dynamic scheduling does not create production schedules. Instead, decentralized production control methods dispatch jobs when necessary and use information available at the moment of dispatching. Such schemes use dispatching rules or other heuristics to prioritize jobs waiting for processing at a resource. Some authors refer to dynamic scheduling schemes as on-line scheduling or reactive scheduling. In the following, the author reviews some research works that are related to dynamic scheduling.

The first study in this area was initialized in 1974 by Holloway and Nelson who implemented a multi-pass procedure in a job-shop by generating schedules periodically. They concluded that a periodic policy (scheduling/rescheduling periodically) is effective in dynamic job-shop environments. In 1982, Muhleman et al, analyzed the periodic scheduling policy in a dynamic and stochastic job-shop system. Their experiments indicate that more frequent revision is needed to obtain better scheduling performance. Yamamoto and Nof (1985) used a regeneration method in developing their scheduling systems in a job shop situation. The method rescheduling the entire set of operation (or jobs) including those unaffected by the change in condition, demand and/or constraints. They compared three scheduling procedures to deal with machine breakdowns. However, they did not address the problems of another uncertainties such as rush order, increased priority and order cancellation.

In 1992, Church and Uzsoy considered periodic and event-driven rescheduling approaches in a single machine production system with dynamic job arrivals. Their results indicate that the performance of periodic scheduling deteriorates as the length of rescheduling period increases and event-driven methods achieve a reasonably good performance.

Li et al. (1993) considered the problem of dynamic scheduling in response to changes that take place on a factory shop-floor. They proposed a heuristic rescheduling algorithm that revises schedules by rescheduling only those operations
that need to be revised. One limitation of the algorithm is that it can only deal with rescheduling when there is no change in existing operation sequence for each machine. They did not consider the alternate operation sequence for rescheduling. They stated that typical event to trigger the rescheduling include machine breakdown, job arrival or cancellation, job priority (or due date) changes, quality problems, over- or underestimate of processing times, shortage material, and being behind or beyond the schedule of transportation, tools or personnel delays. A rescheduling system creates a new schedule by altering the schedule being used and adapting it to the new shop status and production requirements.

In 1999, Sabuncuoglu and Karabuk proposed several reactive scheduling policies to cope with machine breakdowns and processing time variations. Their results indicate that it is not always beneficial to reschedule the operations in response to every unexpected event and the periodic response with an appropriate length can be quite effective in dealing with the interruptions. In 2000, Subramaniam et. al. demonstrated that significant improvements to the performance of dispatching in a dynamic job-shop could be achieved easily through the use of simple machine selection rules. In addition, the reactive scheduling problems have also been studied by implementing knowledge-based methodology, finite state machine, and other artificial intelligence

Vieira, et. al. (2000) described analytical model that predict the performance (such as average flow time and machine utilization) of a single machine system under periodic and event-driven rescheduling strategies in an environment where different job types arrive dynamically and set-ups incurred when production changes from one production to another. A first-in-first-out rule based algorithm was used to reschedule the new jobs up to the rescheduling moment, along with those jobs from the last schedule that did not begin processing.

Sun and Xue, 2001, develop a reactive scheduling method to minimize the scheduling changes for improving the efficiency of reactive scheduling, while maintaining the quality of the overall scheduling. Their main objective of their study is to integrate production scheduling with product design, when design parameter are changed, the manufacturing requirement are then update automatically, when these
manufacturing requirement cannot be satisfied by the current created schedule, change of the production schedule can be conducted simply by canceling the original order and inserting the modified order. They called a match-up reactive scheduling for their approach. In order to responds changes in product orders and manufacturing resources, they also employed the match-up rescheduling approaches. They used some rules to match-up the schedule. Unfortunately, they did not report the effectiveness of their study. Furthermore, the system studied is not clearly desirables.

Diaz et. al. (2003), analyze performance properties of list scheduling algorithms under various dynamic assumptions and different levels of knowledge available for scheduling, considering the case of unit execution time tasks. They focus on bounds for the ISF (immediate successors first) and MISF (maximum number of immediate successors first) scheduling strategies and show the difference from other bounds obtained for the same problem. They also present case studies and experimental results to assess the average behavior.

Liu et al. (2005) analyze the characteristics of the dynamic shop scheduling problem when machine breakdown and new job arrivals occur, and present a framework to model the dynamic shop scheduling problem as a static group-shoptype scheduling problem. Using the proposed framework, they apply a metaheuristic proposed for solving the static shop scheduling problem to a number of dynamic shop scheduling benchmark problems. The authors only implemented tabu Search algorithm for the DMSS problem because the authors believes that many computational experiments have shown that tabu search can compete with all other known metaheuristics by its flexibility and efficiency. The authors conclude that the metaheuristic methodology which has been successfully applied to the static shop scheduling problems can also be applied to solve the dynamic shop scheduling problem efficiently. Unfortunately, the results reveal that the more frequent the dynamic events happen, the more difficult to find the solution equal to the lower bound (LB).

### 2.3.3 Dynamic Scheduling Approaches

Various approaches have been applied to job shop scheduling, including the following: dispatching rules (Panwalkar, 1977), mathematical programming (French, 1982), heuristics (Kusiak, 1990), simulation- based methods (Ramashesh, 1990), and artificial intelligence (AI)-based methods (Geyik, 1997).

It has been recognized that scheduling optimization using mathematical programming is very difficult, because of lengthy computational time. It becomes more difficult to achieve an optimal result when the variety of parameters and constraints is incremented (Maturana, et. al., 1997). Furthermore, job shop scheduling is among the hardest combinatorial optimization problems and is NPcomplete (Garey and Johnson, 1979). After some early successes in the 1950's and 60's, such as Johnson's algorithm for sequencing $n$ jobs on two machines, it was found that even the simplest idealized problems, at the same time as they may be able to be formulated sophisticatedly using integer or dynamic programming require an excessive amount of computation time to solve exactly (Higins and Wirth, 1995). That is, for these problems the fastest currently available algorithms (exact solution methods) are exponential time. In other words, the number of computations required to solve the model exactly grows exponentially with the problem size. So the problem of dimensionality remains and forces to search for heuristics, that is fast (polynomial time) procedures which are near optimal in some sense.

A heuristic has been defined as a method which on the basis of experience or judgment seems likely to yield a good solution to a problem, but which cannot be guaranteed to produce an optimum (Foulds, 1984). The difficulty with applying heuristics to scheduling problems is that it is very difficult to decide which information to ignore. The loss of information takes place in two stages. Firstly in order to build an operations research mode, it needs to ignore some aspects of the real problem. For example, it may assume that set-up times are predictable or that the goal is simple profit maximization and is not affected by any hidden agendas. Secondly, once the model has been formulated, it removes it even further from reality by using a heuristic which may ignore further information (Maturana, et. al. 1997).

Simulation-based methods have also been receiving attention, because of their flexibility and potential to evaluate manufacturing configurations. By applying different dispatching rules, such as earliest due date (EDD), first in, first out (FIFO) or shortest processing time (SPT), the shop-floor performance can be measured. The dispatching rule that attains the highest level of performance (through a simulated model of the shop-floor operations) is favored to drive the production activity. Moreover, these scheduling strategies provide different results that can be compared against each other to select the most suitable policy to achieve a given production requirement, while satisfying the system constraints. As a compromise, AI methods have gained popularity recently for achieving accurate, timely scheduling results (Geyik, 1997).

Artificial intelligence (AI) is the generic name given to the field of computer science dedicated to the development of programs that attempt to replicate human intelligence. Artificial intelligence (AI), the technology that attempts to preserve domain intelligence (knowledge base) in order to use the same for decision making in the future, has matured enough to redirect the research in scheduling. There are several capabilities of AI that make this technology particularly suitable for scheduling; these include the (Liu, et al, 2005):

- richer, more structured, knowledge representation schemes capable of fully incorporating manufacturing knowledge, constraints, state information, and heuristics;
- reasoning ability enabling the scheduling systems to perform more reactive scheduling in addition to predictive scheduling;
- ease of integrating an AI-based scheduler with other decision support systems in the manufacturing environment, such as diagnostic systems, process controllers, sensor monitors, and process-planning systems; and
- ability to incorporate descriptive, organizationally specific scheduling knowledge usually possessed only by human expert schedulers.


### 2.4 Simulation In Scheduling

Simulation is defined as the imitation of the operation of a real world process or system over time (Banks, 1998). Simulation is a necessary problem solving methodology for the solution of many real world problems. Simulation is used to describe and analyze the behavior of a system, as what-if question about the real system, and aid in the design of real systems. Existing system and conceptual system can be modeled with simulation. In other word (Shannon, 1975): simulation is an experimental techniques and applied methodology which seeks (i) to describe the behavior of system, (ii) To construct theories or hypotheses that account for the observed behavior, and (iii) To use these theories to predict future behavior or the effect produced by changes in the operational input set.

Simulation modeling is a highly flexible technique because its models do not require the many simplifying assumption needed by most analytical techniques. Furthermore, simulation tends to be easier to apply than analytic methods. In addition, simulation data is usually less costly than data collected using a real system. However, constructing simulation models may be costly, particularly because they need to be thoroughly verified and validated. Additionally, the cost of the experiment may be increase nature of simulation requires time increases. The statistical nature of simulation requires that many runs of the same model be done to achieve reliable and accurate results. Although its flexibility, simulation modeling traditionally is not an optimization techniques

Simulation can be used to investigate the effect of scheduling rules on the system performance. These models have been developed using:

1. general purpose programming languages (C, FORTRAN, VISUAL BASIC, PASCAL, etc,);
2. general simulation languages (GPSS, SLAM, SIMSCRIPT, etc.);
3. special purpose simulation packages (WITNESS, SIMFACTORY, ARENA, etc.).

Generally, different authors give different statements of the functions of a simulation packages tool, depending mainly on how detailed this statement is. In summary, the
following advantages and disadvantages (Table 2-3) and capabilities and limitation (Table 2-4) of simulation methodology for modeling can be highlighted:

Table 2-3 Advantages and Disadvantages of Simulation
Advantages of Simulation

- Once a model is built, it can be used repeatedly for various analyses.
- Simulation data is usually cheaper than data coming from the real system.
- Simulation methods are usually easier to apply than analytic methods.
- Simulation models do not require the many simplifying assumptions of analytic methods.
- Simulation models may be costly to build.
- Because of its statistical nature, many runs of the same model are necessary to achieve reliable data.
- Once the methodology is well understood, there is the tendency to use it even though analytic techniques would suffice.

Table 2-4 Capabilities and Limitations of Simulation
Capabilities of Simulation

Provide estimates of measures of performance, e.g.:

- Time in the system.
- Worker/Machine utilization.
- Number in queue.
- Time in the queue.

Evaluate the effect of change to system operational parameters:

- Changes to system inputs / resources such as rate of arrival, rate of service.
- Number of material handlings available to move material from one work station to another.


## Table 2-4 <br> Continued

## Limitations of Simulation

- It cannot optimize performance of the system; it can only describe the results of "what-if" scenarios or questions.
- It cannot give accurate results if the inputs are inaccurate.
- It cannot describe characteristic that have not been explicitly modeled.
- It cannot solve problems; it can only provide information from which solution can be inferred.

Simulation is often defined as a methodology for conducting experiments using a model of real system. Simulation is merely a tool for problem solving; by itself, it cannot provide an answer (Pichitlamken and Nelson, 2001)

### 2.4.1 Motivation for Simulation

The motivation to employ simulation is multifold. For example:
(1). Simulation can provide solutions when analytical model fail.
(2). Model to be simulated can represent a real-world process more realistically because fewer restrictive assumptions are required.
(3). More than one performance measure may be evaluated at one time.

Unfortunately, simulation also has drawbacks, for example:
(1). Each run of a stochastic simulation model produce only estimates of a model's true characteristics for a particular set of input parameters.
(2). Simulation can be expensive and time consuming to develop.
(3). The volume of data produced through simulation creates a tendency to place greater confidence in a study's result than is justified.
(4). Validity is difficult to ensure.

### 2.4.2 The Steps of Simulation

Simulation attempts to provide structure and context to decision-making in complex and sometimes chaotic environment. It does this by providing to the decision-maker a rigorous description of the system or process under study. The following decision-making process framework is a hybrid of several published paradigms. Most formal and many informal decision-making situations require the shown as Figure (Law and McComas, 2000). For more detail see Jensen (1999), Schmidt (1986) and Mehta (2000).


Form: Simulation, Modeling and Analysis, Law, A. M. and McComas, M. G. Proceding of the 2000 winter simulation conference, 2000.
Figure 2.4: Simulation Modeling Process

## 1. Need Recognition.

First, one observes a phenomenon to investigate or question to research. At this stage, questions are often ill-defined and may exist as little more than a hunch that something is wrong or needs adjustment.

## 2. Problem Formulation

After a bit of though and some preliminary investigation a specific question or set of question emerge. This step often includes the identification of alternatives and the choice of a criterion by which to make a decision.

## 3. Model Construction

Third, one decides on a context in which to ask formulated question. This may include constructing a mental model, building a physical model, conceptualizing an analog, or developing a mathematical representation of the problem. In this class we shall spend a great deal of time constructing mathematical models but it is vital to note that this activity is but one in the framework. Here, we shall concentrate on computer simulation.

## 4. Data Collection

Data collection describes the mean to generate data input for modeling. There are at least as many ways to generate data as there are modeling techniques. A difficult question that must be answered pertains to the amount of data to be
collected and the level of data aggregation required. Sets of simplifying assumptions are usually required.

## 5. Model Solution

A significant advantage of mathematical models is that once they constructed (and the required data is generated) solution is trivial. In most solution, solution procedures can be routinized and then automated. This is often not the case of mental and physical models.

## 6. Model Reliability and Validity

Once a model is built, a check for reliability is made to insure that multiple solution of the same model yield the same result. After reliability is assured, one may compare the solution with an expectation of reality. If the model behaves as expected then one has some level of confirmation that the model is 'valid". If not, then a return to model construction may be warranted. In same case, model building leads one to ensure their view of reality.

## 7. Interpretation of Result, Implications and Sensitivity Analysis.

A reliable and valid model is useless unless one can interpret its solution and apply that solution to a given situation. Additionally, one may wish to describe the consequence of slight departures from assumption or model parameters. Any "sensitive" aspect of our model will cause significant differences in solution. These aspects must be closely monitored and controlled.

### 2.4.3 Scheduling Through Simulation

Each job may have one or more operations remaining before the completion of the order. The sequence of work centers ("machines") through which a job flows constitutes the job's routing. The routings for various jobs will, in general, vary widely. For example, one job may go first to a lathe, then a milling machine, and finally a drill press, while another job may go to a bender and then to a punch press. The operation required at each machine normally includes a machine setup and actual run time. A given job may involve work on a single piece or on multiple pieces that are processed in a single batch. The shop can be scheduled by means of a simulator. Beginning with the existing state of the shop, the flow of work through the shop can be simulated. Upon completion of all jobs in simulated time, the simulated results can be analyzed. Results may be measured in such terms as the total hours of job tardiness and the total time jobs are in the shop (flow time). If the results appear satisfactory, the sequence of events in simulated time can be taken as the scheduled events. If results are not satisfactory, the shop can be simulated again using different machine capacities or different decision rules. This can continue until a satisfactory schedule is found, or until it is concluded that further search is unwarranted.

The basic simulation cycle is triggered with the completion of an operation. It consists of the following steps:
(1). Determine which machine next finishes an operation.
(2). Assign to the now free machine the highest priority job in the queue.
(3). Move the job that just completed an operation to its next machine, or, if all operations have been completed, remove the job from the shop.

### 2.5 Design of Simulation Experimentation

Simulation-based approaches are derivatives of dispatching rule-based approaches. In a simulation-based scenario, one or more dispatching rules may be used to make a decision when a resources becomes available. Simulation-based
approaches are restricted mostly to a forward scheduling capability (i.e., where a schedule is constructed by starting from a reference time and then advances the simulation clock as jobs are scheduled on resources). Simulation models are able to represent the detail of scheduling situations, and simulation-based approaches are useful in communicating the specific detail to various levels of personnel because of visual aids (e.g., animation) offered by simulation.

From the simulation view point, a job is considered as a queuing network where an order may require several different operations by different machines and may have to wait in several different queues. If job arrive at the shop randomly over time, the job shop is referred to as a dynamic job shop. This chapter present a review of basic factors incorporated into simulation models of dynamic job shops and therefore provide a basic understanding of a job shop simulation model for scheduling analysis. The second goal of this chapter is to provide a basic understanding of scheduling rules and their performance in simulated job shop.

The most likely components of job shop simulation model are as follows:

1. Order arrivals
2. Processing and setup times
3. Machines
4. Job routings
5. Shop load factor
6. Due dates
7. Priority rules

### 2.5.1 Order Arrivals

The arrival of orders is modeled in one of the following ways:

1. Instantaneous release of order into the shop. In this approaches the next order arrival times is defined at the time of each order arrival. The time between these arrivals is defined as a randomly generated variable.
2. Periodical release of all available orders at the beginning of the schedule period (day, week, etc.). This can be modeled in two ways:
a. All the arriving orders as defined above accumulate at an order entry point. All of these orders are released into the shop at predefined points in time.
b. At each order release time, a number defined as random variable of orders is generated.
3. Order pooling. This is similar to the above, except that a subset of the available orders is released into the shop at the beginning of each scheduling period. The selection of orders to be released into the shop may be based on the shop load and order characteristics.
The first approach is used in most models. The most popular arrival pattern is that of the Poisson process (i.e., the Poisson arrival rate or exponentially distributed inter-arrival times). If the time between arrivals is exponentially distributed, the rate (i.e., the number of arrivals per unit time) has a Poisson distribution. Therefore the Poisson-distributed arrival rate (in orders per unit time) is translated into interarrival time of the corresponding exponential distribution. However, when periodic release or order pooling is utilized, the Poisson may directly represent the number of orders arriving in an hour, day, and so on. The Erlang distribution is the sum of exponential distributions and is also used to model order arrivals. Other distributions for the interarrival time or arrival rates are uniform, geometric, binomial, and empirical (actual shop data) distributions. Constant interarrival times also used in investigating shop performance or the sensitivity of shop performance and the priority rules to some order and shop parameter.

The prevalence of the Poisson process is probably a result of its widespread use in queuing theory and its observed validity in some practical situations (e.g., number of calls arriving at a switchboard). The observed distribution of arrivals in actual shops, however, shows a wide variety in the arrival rate, and the Poisson distribution is not sufficient to explain or fit all the distributions observed. If the number of sources generating orders decreases, applicability of the Poisson assumption diminishes. For example, if orders to the shop are generated by distribution center based on minimum order levels, the consolidated order patterns may be erratic, even if the customer order pattern may be a Poisson process.

Several different studies report that the arrival pattern is not important in evaluating the relative effectiveness of priority rules, although shop performance can be affected by the arrival pattern. Studies investigating periodic release and order pooling indicate similar result. In general, shop performance decrease with the increasing variance of the interarrival time distribution. Under periodic release, the following conclusion where obtained in various simulation studies:

1. The mean and variance of the inventory level are higher with an increase in the release period ( Panwalkar, et. al. 1976).
2. Utilization is higher than average at the beginning of a scheduling period but is lower at the end (Panwalkar, et. al. 1976).
3. Fewer jobs are tardy for periodic release; however, the job that are tardy have longer periods of tardiness (Ulgen, O., 1979).
4. Due date performance is improved when period release is combined with a scheduling rule (Holloway and Nelson, 1974).
5. Job pooling (i.e., releasing a subset of orders at predefined intervals) is more restrictive and usually causes a decrease in shop performance (Ulgen, 1979) However, if the subset is selected to be balance the machine workloads, job pooling has a positive effect on shop and workload balance measures but has no significant effect or worse results on variance of lateness distribution and average tardiness (Irastorza and Deane, 1974).

### 2.5.2 Processing and Setup Times

In most job shop simulation models, the processing times are determined when an order arrives at the shop. Two approaches at this point:

1. Generate the actual processing times from a specified distribution; the processing times are random variables from a distribution such as the exponential distribution.
2. Generate the estimate processing times; the estimated times are the information available for scheduling purposes. When an order is placed on a machine, a random variable called a work rate factor is generated and is multiplied by the estimated time to give the actual time required.

The most common distributions are exponential and uniform for the estimated times and triangular, normal, or uniform for the work rate factor. This approach simulates the fact that in most cases the scheduler's knowledge or the processing times is not accurate and the process times fluctuate during day-of-day operations due to uncontrollable factors.

The specified families of processing time distributions are associated parameter affect shop performance. More important, some priority rules, such as SPT, are more sensitive to processing time distributions than are others. In general, as the variability of the order processing time decrease, performance of the non-duedate scheduling rule improves.

The setup times are included in the processing times in most models. In some models dependent setup times are used, the distribution of these times must be selected along with the parameter values. As the variance increases, the desirability for minimizing the setup times increases. The relative values of mean setup time and the mean processing time are also important considerations. When the mean setup time is large with respect to the mean processing time, there are more benefits obtainable from the scheduling rules that minimize the setup times.

In recent models, due to the increased capability and easy of modeling, a sequence-dependent setup time has been used. The presence of sequence-dependent setups changes both shop performance and the performance of the priority rules. Priority rules, which take setup times into consideration, are more successful than the others when the setup times are strongly sequence dependent (e.g., changing from J1 to J2 takes 10 minutes but changing from J3 to J2 takes 120 minutes).

### 2.5.3 Number of Machines

The number of machines used in simulation models varies greatly. In hypothetical models designed to evaluate the performance of scheduling rules, the number of machines range from 4 to 15 . There seem to be a consensus that a fourmachines shop model is large enough so that the result can be extrapolated to the
more complex shops. Some comparative studies have investigated the effect of shop size on the relative effectiveness of the priority rules and conclude with similar result: that neither the size nor the configuration of the shop changes the relative effectiveness of the priority rules.

### 2.5.4 Job Routing

Job routing determines the required sequence of operation so as to predict the traveling pattern of orders among the machines. Diversity of order types is imported to the models via a routing matrix, which defines the transition probabilities of orders from one machine to next. The extreme case are the pure flow shop, where there is only one routing, and the pure job shop, where the transient probabilities between the machines are equal for subsequent operations. Pure job shop models are the most common types of models in simulation studies. This is partly because of the easier load control over the shop in pure job shop models.

Often in real system, some or all orders may have alternative routings such that an operation may be performed on any one of number of machines. Two approaches are possible when alternative routing exist:

1. Place the order in all feasible operation queues. Perform the operation on the first available machine; remove the order from the other queues when the order is assigned to a machine.
2. Assign the order to an idle machine that is capable of performing a feasible operation; if there is no such idle machine, place the order in a queue according to some queue selection rule (e.g., shortest queue length, least work in queue, etc.).

Alternative routing has a significant impact on shop performance and on the relative effectiveness of the priority rules; It provides better performance and reduces the difference between the priority rules.

### 2.5.5 Machine and Shop Utilization

The combined effect of order arrival distribution, job routing, and processing times determine machine utilization. From the standpoint of job shop simulation, machine utilization is important because it affect queue lengths. If the average queue length is too small, the scheduling rules used in the model may not be forced to make discriminating order selections. When this situation occurs, it is difficult or impossible to evaluate the effectiveness of the scheduling rule. Adverse effects also result from machine utilization that is too high. If utilization is near 1.00 , transient conditions may extend over long periods and require excessive CPU time in order to obtain a steady state that permits data to be collected for comparison purposes. Machine utilization commonly found in the literature ranges from 0.85 to 0.95 . Utilizations in this range usually cause queues to reach a length that permits scheduling rules to select an order from several in the queue but does not lead to very long queues.

Sequence-dependent setup times may require careful consideration due to their effect on machine utilization and hence queue lengths. When some scheduling rules yield significantly different average setup times than some other rules, the model results may produce small queues. On the other hand, if another scheduling rule does not consider setup times, the combined setup plus the processing times may cause a saturation of the shop and thus produce an undesirable effect.

### 2.5.6 Due Date

Several different studies indicates that shop performance and the relative effectiveness of priority rules are affected by due date assignment methods as well by the tightness of due dates. The following considerations related to due date assignment:

1. Through policy (fixed) parameters, each order is assigned a due date when it arrives at the shop. The due date assignment method may or may not use current shop information:
a. Static due date assignment rules consider only order data such as the arrival time, routing, and operation processing times of an order. Hence the order allowance time is a fixed amount for a given order of data and does not depend on the shop status when the order arrives.
b. Dynamic due date assignment methods employ order and shop data. In addition to the arrival times, operation times, and routing, other factors in due date determination may include the current shop load and the average waiting time of the orders.
2. Due date assignment and order sequencing decision may be considered together and simultaneously as two dependent factors in the planning process. This leads to a new problem that requires determination of both the optimal set of due date and schedule for a given situation involving the shop status and order parameters.

### 2.5.7 Priority Rules

In the scheduling literature, a variety of terms, such as scheduling rule, priority rule, dispatching rule, or heuristic, refer to the rule that select an order from the order waiting in a queue to be processed next by the machine. However, a distinction is possible for clarification purpose: Usually, a priority rule is defined as a method of assigning a scalar value to each order in a queue fro scheduling purpose. A dispatching rule is defined similarly but implies that after the priorities are assigned, the job with the most priority will be dispatched to an available machine. A heuristic implies that more complex mathematical rules are used in determining the priorities. Finally, a scheduling rule may employ one or more priority rules and/or more complex mathematical or heuristic concepts in determining the next order to be
processed. In practice, the basic term priority or dispatching rule is used for all of the above.

Priority rules may be classified according to their time dependency (static versus dynamic rules), the type of data they use (local versus global rules), or both. A static rule determines only one priority value for each operation of an order during its existence in the shop. A dynamic priority value, in contrast, change over time, to assign the right order (i.e., the order that has the highest actual priority) to an available machine. The priority values of order must be updated before each decision is made. Hence more calculation is involved in dynamic rules. Adam and Surkis (1980). Priority update interval and anomalies in dynamic ratio type job shop scheduling rules, investigated the effect of updating policy and of updating the intervals on computational requirements and the effectiveness of priority rules. They concluded that due date performance is sensitive to the updating policy and to the updating intervals especially at high utilization (i.e., 92 to 96\%).

Panwalkar and Iskander (2001) describe and categorized 113 priority rules. The functional categorization is given below.

1. (a). Simple priority rules are based on order and/or shop data such as processing times, due date number of operations, cost(values), setup times, arrival times, and slack.
(b). The combinations of simple priority rules are the applications of two or more priority rules with the selection of which rule to use at a specific time being a function of the queue and order characteristics.
(c). Weighted priority rules involve the application of rules in 1(a) and/or 1(b) combined with different weights.
2. Heuristic involve more complex considerations, such as the solving of static problem at the beginning of each scheduling period, look-ahead, and so on.
3. Other rules.

The body of job shop simulation research established the validity of the basic assumption that given all the other shop parameters are the same, shop performance
is strongly affected by the priority rules being used. However, there is no clear winner claimed for all the performance measures.

### 2.6 Simulation and Its Application on Scheduling

Mathematical models are a formalism whereby we can summarize our understanding of the physical world and utilize this knowledge in calculations of engineering interest. An important feature of any model is that it accurately reflects only those phenomena relevant to the current activity. On the one hand, accuracy is crucial to the utility of the results, and, on the other, relevance avoids unnecessary computation in achieving results and avoids obscuring important conclusions in the details.

Simulation is defined as the imitation of the operation of a real world process or system over time (Banks, 1998). Simulation is a necessary problem solving methodology for the solution of many real world problems. Simulation is used to describe and analyze the behavior of a system, as what-if question about the real system, and aid in the design of real systems. Existing system and conceptual system can be modeled with simulation. In other word (Shannon, 1975): simulation is an experimental techniques and applied methodology which seeks (i) to describe the behavior of system, (ii) To construct theories or hypotheses that account for the observed behavior, and (iii) To use these theories to predict future behavior or the effect produced by changes in the operational input set.

Many researches has used simulation methodology to solved scheduling problems (Yang and Wang, 2001, Cheng, Gen, and Tsujimura, 1996, Fonseca and Navaresse, 2002, Maturana, et. al. , 1997, Kacem, Hammadi, and Borne, 2002, Ying, 1996, and Sadeh and Fox, 1996.) Karatza, 2000, Chong and Sivakumar, 2003. In Term of Dynamic Simulation (Maturana, et al., 1997, Kacem, Hammadi and Borne, 2002, Ying, 1996, and Sadeh and Fox, 1996.). or Stochastic Simulation Yang and Wang, 2001, Fonseca and Navaresse, 2002.

Simulation modeling is a highly flexible technique because its models do not require the many simplifying assumption needed by most analytical techniques. Furthermore, simulation tends to be easier to apply than analytic methods. In addition, simulation data is usually less costly than data collected using a real system. However, constructing simulation models may be costly, particularly because they need to be thoroughly verified and validated. Additionally, the cost of the experiment may be increase nature of simulation requires time increases. The statistical nature of simulation requires that many runs of the same model be done to achieve reliable and accurate results. Although its flexibility, simulation modeling traditionally is not an optimization techniques

Simulation system has become a powerful decision making instrument for scheduling. It requires a few simplifying assumptions, captures many of the true characteristics of the real model, and provides good insights about the interactions and relationships between qualitative and quantitative variables. This section describe recent research on simulation in scheduling by many authors.

Chong and Sivakumar, (2003) presented A simulation-based real-time scheduling mechanism for dynamic discrete manufacturing. The authors use mean flow time performance for different scheduling approaches, subjects to disturbances such as machine breakdowns. Discrete event simulation is used on-line to evaluate the selected approaches and the corresponding schedules to determine the best solution. The authors conclude that discrete event simulation has been an essential tool for detailed scheduling under a highly dynamic and unpredictable manufacturing system.

Cave, Nahavandi, and Kouzani (2002) introduce simulated annealing for simulation optimization of a real scheduling problem in industry. The authors showed that when using this method, high quality schedules can be produced within reasonable time constraints, but still not less computational yet.

Karatza (2000) Studied scheduling simulation model to address performance issues associated with scheduling. Three policies which combine processor and I/O scheduling are used to schedule parallel jobs for a variety of workloads. Simulated results reveal that all scheduling methods have merit, but one method significantly
improves the overall performance and also provides a guarantee for fairness in individual job execution.

### 2.5 ANN for Solving Scheduling Problems

An artificial neural network (ANNs) is one of the AI techniques that have gained an important role in solving problems with extreme difficult or unknown analytical solutions (Lawrence, 1994). An ANN consists of an interconnected web of special units, called neurons, with associated connection weights that, after receiving a proper training, are capable of achieving a desired response to new inputs. Its ability of learning from examples makes ANN an extremely powerful programming tool when domain rules are not completely certain or when some amount of inaccuracy or conflicting data exist (Medsker, 1994). An ANN is used to learn a functional relationship between a set of jobs and the corresponding to the set of machine in the shop that optimize the stated performance criterion. The 'trained' neural network is then able to apply the learnt relationship to new problems.

There are some approaches developed based on artificial intelligence techniques such as neural networks, expert systems, fuzzy logic and genetic algorithms. There are some approaches developed based on artificial intelligence techniques such as neural networks, expert systems, fuzzy logic and genetic algorithms. Among them, Bilkay et al. (2004) proposed algorithm for flexible manufacturing system by using fuzzy logic. Yu and Ling (2001) involved neural network and genetic algorithm to solve the expanded job-shop scheduling problem. Genetic algorithms (GAs) are also used independently for JSS by some researches, among them Brizuela and Sannomiya (1999), Madureira and Ramos, (2001), Zhou et al. (2001). Watanabe, 2003 using ANN for solves Job shop scheduling.

Sabuncuoglu and Gurgun (1996) propose a new neural network approach to solve the single machine mean tardiness scheduling problem and the minimum makespan job shop scheduling problem. The proposed network combines the characteristics of neural networks and algorithmic approaches. The performance of
the network is compared with the existing scheduling algorithms under various experimental conditions. A comprehensive bibliography is also provided in the paper.

El-Bouri et al. (2000) presented an approach for single machine job sequencing problems that is based on artificial neural networks. A problem is classified first by one type of neural network into one of a number of categories. The categorization is based on the problems characteristics. Then another neural network, which is specialized for a particular category, applies a previously learning relationship to produce a job sequence that aims to better satisfy the given objective. The learning is acquired in these networks after a training process in which the network is exposed repeatedly to a set of example problems and their solutions. The trained network thereby learns predominant relationships between given problems, and the output sequences that optimally meet the desired objective. The advantage of such an approach is that it allows what amounts to a "customized" heuristic to be established for problem subsets and various objectives without having to deduce an algorithm in advance. The methodology and its implementation is described for several of the more common sequencing objectives, as well as for a hypothetical objective that minimizes a cost function exhibiting a limited exponential behavior.

Lee and Shaw (2000) consider the classic problem of sequencing a set of jobs that arrive in different combinations over time in a manufacturing flow-shop. They focus on the development of a two-level neural network that incrementally learns sequencing knowledge. Based on the knowledge gained from learning using a set of training exemplars, the neural network makes real time sequencing decisions for a set of jobs that arrive in different job combinations. In addition to explain the details regarding the workings of the neural network, they also evaluate its performance for flow-shop sequencing problems. The practical benefit of the neural-net approach is that the neural network incrementally learns the sequencing knowledge and can apply the knowledge for sequencing a set of jobs on a real time basis. They also show that the neural network can be used to develop hybrid genetic algorithms. The experimental results demonstrate that (1) the neural-net approach produces consistently superior solution quality (i.e., makespan) with significantly less computational time than the traditional heuristic approaches; (2) when compared to
genetic algorithms the neural-net approach's performances are within 3.4\% of those of genetic algorithms, but using only less than $0.2 \%$ of the computational time needed by genetic algorithms; and (3) the neural-net approach further improves solution quality and computational time by combining it with genetic algorithms.

Yang and Wang (2001), presented a new adaptive neural network and heuristics hybrid approach for job-shop scheduling is presented. The neural network has the property of adapting its connection weights and biases of neural units while solving the feasible solution. Two heuristics are presented, which can be combined with the neural network. One heuristic is used to accelerate the solving process of the neural network and guarantee its convergence; the other heuristic is used to obtain non-delay schedules from the feasible solutions gained by the neural network. Computer simulations have shown that the proposed hybrid approach is of high speed and efficiency. The strategy for solving practical job-shop scheduling problems is provided.

Yu and Liang (2001), presented a hybrid approach involving neural network and genetic algorithm (GA) to solve the expanded job-shop scheduling problem (EJSSP). The GA is used for optimization of sequence and a neural network (NN) is used for optimizing of operation start times with a fixed sequence. The authors reported that the approach has been shown powerful for competes expanded job-shop scheduling problem.

### 2.5 Summary of Chapter 2

This chapter has provided a broad and specific review on issues related to scheduling. In particular, scheduling classification and scheduling rules were reviewed to provide general background information on the field of study. It also provides specific reviews on job shop scheduling and dynamic scheduling since these are the focus problem in this study. This reviews also covered previous studies conducted by various researchers on dynamic scheduling. Background on the simulation techniques and its application in scheduling studies were also reviewed.

In addressing the dynamic job shop scheduling problem, close-form mathematical and optimization procedures would have difficulty in capturing the complexities and not capable to provide solution in a reasonable amount of time. Artificial neural network has been identified as a promising information processing tools in many fields of studies. Its applications in solving scheduling problems were also reviewed in this report.

## CHAPTER 3

## RESEARCH METHODOLOGY

This chapter describes the methodology adopted in this research. It begins with description of the traditional and proposed frameworks for producing production schedules. Then it describes the operational framework, research questions and development phases.

### 3.1 Traditional and Proposed Framework

Since the job shop scheduling problem is a well-known NP hard problem, a realistic size of the problem can not be solved by searching and evaluating all the alternative solutions. Generally, there are no optimization algorithms which can solve a NP hard problem in a polynomial time. However, such problem may be solved using heuristics algorithms with approximated optimal solution. There are many literatures which report various heuristic methods to solve such problems. One alternative technique is through simulation. This approach has been extensively applied in many application areas including the job shop-scheduling problem. The main problem in applying this approach is that the user needs to re-run the simulation whenever there are changes in the system. This traditional approach is time consuming and not practical for a dynamically changing manufacturing environment.

Thus, this study proposes a new theoretical framework for addressing the need of rescheduling in dynamic environment as shown in Figure 3-2.


Figure 3-1: Traditional Theoretical Framework


Figure 3-2: Proposed Theoretical Framework

### 3.2 Operational Framework

Figure 3-3 shows the intended operational framework of the proposed scheduling system. It shows the relationships among the scheduling system, user (production scheduler) and manufacturing processes. Assuming a manufacturing system begins its operation following an initial schedule prepared according to the
present job shop condition. However, when changes emerge in demand or capacity, the production scheduler has to immediately update the system with new information. Then, the scheduling system would instantaneously generate the revised schedules without a need to evaluate or simulate the new manufacturing scenarios.


Figure 3-3: Operational Framework

### 3.3 Research Questions

The literature reviews as discussed in Chapter 2 reveal some research questions regarding potential and applicability of neural network technique in development of a scheduling system for a dynamic job shop. Among the unanswered question are:

- Can ANN supplement or replace the existing method in the process of generating schedules?
- Can ANN supplement or replace the existing method for selecting the best schedule/decision for a given set of conditions for dynamic job shop scheduling?

This research also seeks to address the above questions.

### 3.4 Development Phases

The development phases used in this study comprises two phases as shown in
Figure 3-4:
Phase 1: Simulation studies of various scheduling scenarios.
Phase 2: Design and development of a dynamic scheduling system by using artificial neural network (ANN).


Figure 3-4: Development Phases

## CHAPTER 4

## MODEL DEVELOPMENT

### 4.1 Problem Definition

A case study of 6 by 6 job shop scheduling problem from Fisher and Thompson (1963) was adapted in this study since the same case study has been widely referred by other researchers. The case study is shown in Table 4-1. For the purpose of this research, uncertainty elements were added to the original data set. This job shop consists of six machines, labeled as A, B, C, D, E, and F. The tasks were to manufacture six different parts.

Table 4-1 A case study of $6 \times 6$ job shop scheduling problem (Fisher and Thompson, 1963).

|  | Operation No |  |  |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :---: | :---: | :---: |
| Job No. | 1 | 2 | 3 | 4 | 5 | 6 |  |  |  |
| 1 | C,3 | A,10 | B,9 | D,5 | F,3 | E,10 |  |  |  |
| 2 | B,6 | C,8 | E,1 | F,5 | A,3 | D,3 |  |  |  |
| 3 | C,1 | D,5 | F,5 | A,5 | B,9 | E,1 |  |  |  |
| 4 | B,7 | A,5 | C,4 | D,3 | E,1 | F,3 |  |  |  |
| 5 | C,6 | B,11 | E,7 | F,8 | A,5 | D,4 |  |  |  |
| 6 | B,3 | D,10 | F,8 | A,9 | E,4 | C,9 |  |  |  |

This job shop was modeled using ARENA simulation software which run on Pentium IV personal computer. The simulation model was designed to simulate the six-machine with each machine adopting similar dispatching rule. The job to be processed by a machine is selected from its respective queue. The physical system configuration is shown in Figure 4-1.


Figure 4-1: Physical configuration of a six-machine dynamic job shop.

Figure 4.1 shows each job comes directly through an entrance gate and passes to various machine according to its predetermined route. Each incoming job will posses a specific task characteristic assigned before entering the job shop. The task characteristics for each job are as the following:

- Routings details
- Job processing time on each machine where operation will be performed
- Scheduling rule


## 4-2 Simulation Model

As noted earlier, a computer simulation model to represent the job shop system was designed using ARENA. The performances of various job shop conditions when using scheduling rules, namely, first-in-first-out (FIFO), earliest-due-date (EDD), and shortest processing time (SPT) were evaluated.

The job shop used in this study consists of 6 unique work centers. The jobs were planned to arrive continuously with inter-arrival times generated from an empirical discrete distribution. The mean value chosen was chosen to create a certain expected shop utilization rate. Each job underwent 6 operations which were drawn from a normal distribution with means extracted from the original data (Fisher and Thompson,1963). The schedule adopted a pure job shop routing whereby when a job left a work center, it was equally likely to go to each of the other work centers. Work center processing times were drawn from a normal distribution with means extracted from Fisher and Thompson (1963). Other assumptions adopted in the development of the model are :

- the resources were available continuously
- preemption of a job was not allowed
- set-up times were included in the processing times
- transportation times were excluded, and
- processing times of the jobs were known after their arrivals at the shop.


### 4.2.1 Steady-state Condition of the Shop (Warm up period)

In order to ascertain when the system has achieved a steady state, the shop parameters, such as the machine utilization level and mean flow-time of jobs need to be observed. It was found that the simulated system reached a steady state after the arrival of about 500 time units.

### 4.2.2 Run Length and Number of Replications

Job arrivals were generated using an exponential distribution. Three machine utilization levels, namely, "low", "medium", and "high" were studied. Thus, in all, for one type of process time distribution, one due date setting and three different utilization levels would resulted in a total of three experimental sets for every dispatching rule. Hence, for the three scheduling rules (FCFS, EDD and SPT), a total of nine simulation experiments were conducted. Each simulation experiment was replicated in twenty different runs. In each run, the job shop was continuously loaded with job orders that were numbered on arrival.

### 4.3 Artificial Neural Network Model

The construction of the artificial neural network (ANN) model involves a learning process. Figure 4-2 illustrates the neural network model developed for this research. The network was developed using a multilayer perceptron (MLP) architecture and the learning process was based on back-propagation algorithm. The datasets for training and testing were stored in a text file. The ANN learning involves computation of the predicted output against the target output. Adjustment of the weight was made to minimize the mean absolute error (MAE) as shown in Figure 43.


Figure 4-2, ANN Scheduling Model


Figure 4-3, Error Adjusted for ANN model.

### 4.4 Sequence Codification Scheme (SCS)

The ANN structure with one input layer, one hidden layer, and one output layer as shown in Figure 4-2 was used in this study. Data representation is an important issue that directly influences the decision on the ANN architecture, specifically, the number of input neurons. The number of input neurons required to represent any given job sequence depends on the definition of these sequence codification scheme (SCS). The codification rules adopted in this research was based on the guidelines proposed by Lawrence (1994). A brief description of the SCS is provided in the Appendix E.

## CHAPTER 5

## RESULTS AND DISCUSSION

### 5.1 Simulation Results

This chapter provides training results for the ANN scheduling model. Tables 5.1 to 5.9 present the results for FIFO, EDD, and SPT scheduling rules with the respective "Low", "Medium", and "High" job arrivals. Appendix B provides the flowcharts for FIFO, SPT, and EDD algorithm.

### 5.2 ANN Training Results

The scheduling scenarios evaluated through ARENA simulation provided valuable input data sets and they were used for training the ANN scheduling model. Detailed results from ARENA simulation are provided in Appendix D.

The training parameters used for the ANN model is shown in Table 5-10. A total of 180 training samples were used with a learning rate $=0.1$.

Table 5-1 Simulation Results where Scheduling Rule = FIFO, Job Arrival = "Low"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | $J 5$ | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 7 | 11 | 16 | 9 | 11 | 16 | 68.529 | 69.832 | 73.097 | 71.524 | 63.000 | 66.417 | 0.311 | 0.191 | 0.196 | 0.190 | 0.309 | 0.340 | 0.033 | 0.046 | 0.027 | 0.010 | 0.083 | 0.146 |
| 9 | 13 | 20 | 9 | 18 | 11 | 60.333 | 77.491 | 75.917 | 87.158 | 80.251 | 65.973 | 0.336 | 0.259 | 0.270 | 0.210 | 0.341 | 0.371 | 0.024 | 0.812 | 0.093 | 0.020 | 0.120 | 0.090 |
| 12 | 18 | 12 | 13 | 20 | 16 | 56.377 | 132.640 | 88.820 | 111.280 | 132.210 | 83.092 | 0.340 | 0.273 | 0.306 | 0.189 | 0.390 | 0.401 | 0.031 | 0.086 | 0.093 | 0.013 | 0.167 | 0.261 |
| 10 | 14 | 9 | 13 | 25 | 4 | 57.845 | 69.990 | 77.711 | 67.263 | 89.552 | 58.189 | 0.260 | 0.252 | 0.286 | 0.173 | 0.324 | 0.300 | 0.012 | 0.087 | 0.016 | 0.027 | 0.049 | 0.052 |
| 12 | 17 | 14 | 15 | 12 | 11 | 68.311 | 79.969 | 69.770 | 80.000 | 82.124 | 67.149 | 0.366 | 0.291 | 0.264 | 0.217 | 0.397 | 0.404 | 0.166 | 0.090 | 0.035 | 0.160 | 0.052 | 0.052 |
| 12 | 9 | 11 | 13 | 14 | 11 | 68.163 | 68.151 | 65.722 | 69.000 | 82.406 | 58.367 | 0.269 | 0.226 | 0.207 | 0.198 | 0.323 | 0.340 | 0.029 | 0.062 | 0.029 | 0.042 | 0.037 | 0.051 |
| 10 | 14 | 14 | 16 | 11 | 13 | 55.598 | 67.281 | 81.452 | 68.888 | 74.928 | 65.774 | 0.350 | 0.260 | 0.256 | 0.206 | 0.367 | 0.410 | 0.020 | 0.078 | 0.042 | 0.088 | 0.056 | 0.066 |
| 8 | 8 | 12 | 11 | 12 | 13 | 60.000 | 69.506 | 61.044 | 68.956 | 61.000 | 63.622 | 0.270 | 0.170 | 0.184 | 0.145 | 0.257 | 0.299 | 0.007 | 0.038 | 0.030 | 0.017 | 0.074 | 0.021 |
| 10 | 11 | 9 | 17 | 10 | 10 | 64.448 | 78.695 | 64.777 | 110.760 | 103.880 | 74.135 | 0.274 | 0.230 | 0.218 | 0.180 | 0.313 | 0.353 | 0.025 | 0.036 | 0.046 | 0.026 | 0.091 | 0.175 |
| 16 | 11 | 16 | 9 | 11 | 10 | 62.166 | 67.548 | 71.529 | 61.000 | 89.959 | 84.386 | 0.316 | 0.230 | 0.202 | 0.228 | 0.337 | 0.354 | 0.019 | 0.056 | 0.067 | 0.179 | 0.072 | 0.031 |
| 12 | 13 | 14 | 14 | 12 | 10 | 83.254 | 70.049 | 71.467 | 75.522 | 74.000 | 66.199 | 0.308 | 0.242 | 0.230 | 0.204 | 0.339 | 0.356 | 0.027 | 0.063 | 0.054 | 0.028 | 0.057 | 0.108 |
| 9 | 10 | 13 | 13 | 12 | 11 | 63.161 | 90.497 | 64.359 | 80.320 | 67.436 | 68.003 | 0.296 | 0.209 | 0.230 | 0.188 | 0.310 | 0.335 | 0.050 | 0.029 | 0.090 | 0.014 | 0.068 | 0.068 |
| 10 | 19 | 14 | 11 | 13 | 13 | 75.936 | 89.083 | 72.743 | 95.162 | 83.691 | 70.543 | 0.335 | 0.267 | 0.270 | 0.175 | 0.371 | 0.390 | 0.063 | 0.075 | 0.121 | 0.021 | 0.126 | 0.124 |
| 8 | 15 | 16 | 14 | 16 | 10 | 61.516 | 96.991 | 120.210 | 97.744 | 102.460 | 106.620 | 0.316 | 0.251 | 0.265 | 0.196 | 0.373 | 0.360 | 0.090 | 0.069 | 0.061 | 0.016 | 0.168 | 0.172 |
| 8 | 13 | 7 | 12 | 14 | 14 | 52.967 | 69.807 | 65.975 | 71.000 | 64.137 | 77.115 | 0.260 | 0.219 | 0.227 | 0.167 | 0.312 | 0.346 | 0.014 | 0.032 | 0.040 | 0.013 | 0.042 | 0.144 |
| 12 | 12 | 10 | 11 | 12 | 19 | 67.873 | 69.600 | 70.897 | 74.158 | 81.617 | 67.269 | 0.318 | 0.221 | 0.224 | 0.178 | 0.321 | 0.355 | 0.016 | 0.044 | 0.049 | 0.018 | 0.051 | 0.102 |
| 10 | 12 | 10 | 13 | 11 | 10 | 65.000 | 76.149 | 93.537 | 56.862 | 64.884 | 68.924 | 0.267 | 0.216 | 0.206 | 0.163 | 0.299 | 0.332 | 0.029 | 0.035 | 0.063 | 0.021 | 0.057 | 0.079 |
| 12 | 13 | 13 | 15 | 12 | 18 | 62.475 | 73.529 | 70.889 | 67.263 | 76.113 | 69.287 | 0.335 | 0.262 | 0.228 | 0.208 | 0.369 | 0.420 | 0.027 | 0.039 | 0.036 | 0.019 | 0.085 | 0.162 |
| 11 | 11 | 14 | 13 | 16 | 12 | 65.822 | 73.404 | 73.687 | 68.021 | 76.632 | 71.379 | 0.308 | 0.730 | 1.250 | 0.792 | 2.817 | 1.620 | 0.015 | 0.037 | 0.064 | 0.040 | 0.144 | 0.083 |
| 6 | 14 | 7 | 16 | 10 | 7 | 73.038 | 76.691 | 75.000 | 74.041 | 82.396 | 62.999 | 0.488 | 0.411 | 0.981 | 0.330 | 2.080 | 1.420 | 0.256 | 0.205 | 0.211 | 0.153 | 0.300 | 0.309 |

$\mathrm{Jn}=\mathrm{Job} \# 1 \quad \mathrm{MA}=$ Machine A
$\mathrm{Jn}=\mathrm{Job} \# 2 \quad \mathrm{MB}=$ Machine B
Jn = Job \#3 $\quad$ MC = Machine C
$\mathrm{Jn}=\mathrm{Job}$ \#4 $\quad \mathrm{MD}=$ Machine D
$\begin{array}{ll}\text { Jn }=\text { Job \#5 } & \text { ME }=\text { Machine E } \\ \text { Jn }=\text { Job \#6 } & \text { ME }=\text { Machine F }\end{array}$

Table 5-2 Simulation Results where Scheduling Rule = EDD, Job Arrival = "Low"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF | F |
| 8 | 13 | 17 | 11 | 13 | 18 | 69.529 | 71.832 | 74.097 | 73.524 | 65.000 | 68.417 | 0.344 | 0.258 | 0.229 | 0.257 | 0.376 | 0.407 | 0.034 | 0.048 | 0.028 | 0.012 | 0.085 | 0.148 |
| 11 | 15 | 23 | 12 | 19 | 12 | 63.333 | 80.491 | 77.917 | 89.158 | 81.251 | 66.973 | 0.436 | 0.359 | 0.337 | 0.277 | 0.374 | 0.404 | 0.027 | 0.815 | 0.095 | 0.022 | 0.121 | 0.091 |
| 15 | 20 | 15 | 14 | 22 | 17 | 59.377 | 133.640 | 91.820 | 113.280 | 134.210 | 84.092 | 0.440 | 0.306 | 0.406 | 0.256 | 0.457 | 0.434 | 0.034 | 0.087 | 0.096 | 0.015 | 0.169 | 0.262 |
| 11 | 17 | 9 | 16 | 25 | 4 | 57.845 | 72.990 | 78.711 | 70.263 | 89.552 | 58.189 | 0.260 | 0.352 | 0.319 | 0.273 | 0.324 | 0.300 | 0.012 | 0.090 | 0.017 | 0.030 | 0.049 | 0.052 |
| 14 | 20 | 16 | 16 | 14 | 11 | 70.311 | 80.969 | 71.770 | 83.000 | 84.124 | 67.149 | 0.433 | 0.324 | 0.331 | 0.317 | 0.464 | 0.404 | 0.168 | 0.091 | 0.037 | 0.163 | 0.054 | 0.052 |
| 14 | 9 | 14 | 14 | 15 | 11 | 71.163 | 69.151 | 67.722 | 69.000 | 83.406 | 58.367 | 0.369 | 0.259 | 0.274 | 0.198 | 0.356 | 0.340 | 0.032 | 0.063 | 0.031 | 0.042 | 0.038 | 0.051 |
| 13 | 14 | 15 | 18 | 12 | 13 | 56.598 | 69.281 | 84.452 | 68.888 | 75.928 | 65.774 | 0.383 | 0.327 | 0.356 | 0.206 | 0.400 | 0.410 | 0.021 | 0.080 | 0.045 | 0.088 | 0.057 | 0.066 |
| 11 | 11 | 13 | 13 | 13 | 13 | 61.000 | 71.506 | 64.044 | 71.956 | 62.000 | 63.622 | 0.303 | 0.237 | 0.284 | 0.245 | 0.290 | 0.299 | 0.008 | 0.040 | 0.033 | 0.020 | 0.075 | 0.021 |
| 11 | 12 | 11 | 19 | 13 | 13 | 66.448 | 80.695 | 65.777 | 111.760 | 106.880 | 77.135 | 0.341 | 0.297 | 0.251 | 0.213 | 0.413 | 0.453 | 0.027 | 0.038 | 0.047 | 0.027 | 0.094 | 0.178 |
| 19 | 12 | 18 | 9 | 11 | 11 | 64.166 | 67.548 | 74.529 | 62.000 | 89.959 | 85.386 | 0.383 | 0.230 | 0.302 | 0.261 | 0.337 | 0.387 | 0.021 | 0.056 | 0.070 | 0.180 | 0.072 | 0.032 |
| 12 | 16 | 14 | 14 | 12 | 10 | 83.254 | 70.049 | 71.467 | 78.522 | 74.000 | 66.199 | 0.308 | 0.242 | 0.230 | 0.304 | 0.339 | 0.356 | 0.027 | 0.063 | 0.054 | 0.031 | 0.057 | 0.108 |
| 10 | 12 | 14 | 16 | 12 | 11 | 64.161 | 93.497 | 65.359 | 82.320 | 67.436 | 68.003 | 0.329 | 0.309 | 0.263 | 0.255 | 0.310 | 0.335 | 0.051 | 0.032 | 0.091 | 0.016 | 0.068 | 0.068 |
| 12 | 21 | 17 | 12 | 14 | 13 | 78.936 | 90.083 | 74.743 | 97.162 | 84.691 | 70.543 | 0.435 | 0.300 | 0.337 | 0.242 | 0.404 | 0.390 | 0.066 | 0.076 | 0.123 | 0.023 | 0.127 | 0.124 |
| 8 | 15 | 16 | 14 | 19 | 13 | 61.516 | 96.991 | 120.210 | 97.744 | 105.460 | 109.620 | 0.316 | 0.251 | 0.265 | 0.196 | 0.473 | 0.460 | 0.090 | 0.069 | 0.061 | 0.016 | 0.171 | 0.175 |
| 11 | 14 | 9 | 13 | 16 | 15 | 54.967 | 70.807 | 68.975 | 72.000 | 66.137 | 78.115 | 0.327 | 0.252 | 0.327 | 0.200 | 0.379 | 0.379 | 0.016 | 0.033 | 0.043 | 0.014 | 0.044 | 0.145 |
| 12 | 15 | 10 | 13 | 14 | 22 | 67.873 | 71.600 | 70.897 | 77.158 | 83.617 | 70.269 | 0.318 | 0.288 | 0.224 | 0.278 | 0.388 | 0.455 | 0.016 | 0.046 | 0.049 | 0.021 | 0.053 | 0.105 |
| 11 | 14 | 11 | 13 | 11 | 10 | 66.000 | 76.149 | 94.537 | 58.862 | 64.884 | 68.924 | 0.300 | 0.216 | 0.239 | 0.230 | 0.299 | 0.332 | 0.030 | 0.035 | 0.064 | 0.023 | 0.057 | 0.079 |
| 14 | 15 | 16 | 18 | 14 | 21 | 65.475 | 76.529 | 72.889 | 69.263 | 78.113 | 72.287 | 0.435 | 0.362 | 0.295 | 0.275 | 0.436 | 0.520 | 0.030 | 0.042 | 0.038 | 0.021 | 0.087 | 0.165 |
| 11 | 11 | 17 | 14 | 18 | 13 | 68.822 | 74.404 | 73.687 | 68.021 | 78.632 | 72.379 | 0.408 | 0.763 | 1.250 | 0.792 | 2.884 | 1.653 | 0.018 | 0.038 | 0.064 | 0.040 | 0.146 | 0.084 |
| 6 | 14 | 7 | 16 | 10 | 7 | 73.038 | 76.691 | 75.000 | 74.041 | 82.396 | 62.999 | 0.488 | 0.411 | 0.981 | 0.330 | 2.080 | 1.420 | 0.256 | 0.205 | 0.211 | 0.153 | 0.300 | 0.309 |


| Jn $=$ Job \#1 | MA $=$ Machine A |
| :--- | :--- |
| Jn $=$ Job \#2 | MB $=$ Machine B |
| Jn $=$ Job \#3 | MC $=$ Machine C |
| Jn $=$ Job \#4 | MD $=$ Machine D |
| Jn $=$ Job \#5 | ME $=$ Machine E |
| Jn $=$ Job \#6 | ME $=$ Machine F |

Table 5-3 Simulation Results where Scheduling Rule $=$ SPT, Job Arrival $=$ "Low"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | $J 5$ | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 6 | 9 | 15 | 7 | 9 | 14 | 67.529 | 67.832 | 72.097 | 69.524 | 61.000 | 64.417 | 0.278 | 0.124 | 0.163 | 0.123 | 0.242 | 0.273 | 0.032 | 0.043 | 0.026 | 0.008 | 0.081 | 0.144 |
| 7 | 11 | 17 | 6 | 17 | 10 | 57.333 | 74.491 | 73.917 | 85.158 | 79.251 | 64.973 | 0.236 | 0.159 | 0.203 | 0.143 | 0.308 | 0.338 | 0.021 | 0.809 | 0.091 | 0.018 | 0.119 | 0.089 |
| 9 | 16 | 9 | 12 | 18 | 15 | 53.377 | 131.640 | 85.820 | 109.280 | 130.210 | 82.092 | 0.240 | 0.240 | 0.206 | 0.122 | 0.323 | 0.368 | 0.028 | 0.085 | 0.090 | 0.011 | 0.165 | 0.260 |
| 9 | 11 | 9 | 10 | 25 | 4 | 57.845 | 66.990 | 76.711 | 64.263 | 89.552 | 58.189 | 0.260 | 0.152 | 0.253 | 0.073 | 0.324 | 0.300 | 0.012 | 0.084 | 0.015 | 0.024 | 0.049 | 0.052 |
| 10 | 14 | 12 | 14 | 10 | 11 | 66.311 | 78.969 | 67.770 | 77.000 | 80.124 | 67.149 | 0.299 | 0.258 | 0.197 | 0.117 | 0.330 | 0.404 | 0.164 | 0.089 | 0.033 | 0.157 | 0.050 | 0.052 |
| 10 | 9 | 8 | 12 | 13 | 11 | 65.163 | 67.151 | 63.722 | 69.000 | 81.406 | 58.367 | 0.169 | 0.193 | 0.140 | 0.198 | 0.290 | 0.340 | 0.026 | 0.061 | 0.027 | 0.042 | 0.036 | 0.051 |
| 7 | 14 | 13 | 14 | 10 | 13 | 54.598 | 65.281 | 78.452 | 68.888 | 73.928 | 65.774 | 0.317 | 0.193 | 0.156 | 0.206 | 0.334 | 0.410 | 0.019 | 0.076 | 0.039 | 0.088 | 0.055 | 0.066 |
| 5 | 5 | 11 | 9 | 11 | 13 | 59.000 | 67.506 | 58.044 | 65.956 | 60.000 | 63.622 | 0.237 | 0.103 | 0.084 | 0.045 | 0.224 | 0.299 | 0.006 | 0.036 | 0.027 | 0.014 | 0.073 | 0.021 |
| 9 | 10 | 7 | 15 | 7 | 7 | 62.448 | 76.695 | 63.777 | 109.760 | 100.880 | 71.135 | 0.207 | 0.163 | 0.185 | 0.147 | 0.213 | 0.253 | 0.023 | 0.034 | 0.045 | 0.025 | 0.088 | 0.172 |
| 13 | 10 | 14 | 9 | 11 | 9 | 60.166 | 67.548 | 68.529 | 60.000 | 89.959 | 83.386 | 0.249 | 0.230 | 0.102 | 0.195 | 0.337 | 0.321 | 0.017 | 0.056 | 0.064 | 0.178 | 0.072 | 0.030 |
| 12 | 10 | 14 | 14 | 12 | 10 | 83.254 | 70.049 | 71.467 | 72.522 | 74.000 | 66.199 | 0.308 | 0.242 | 0.230 | 0.104 | 0.339 | 0.356 | 0.027 | 0.063 | 0.054 | 0.025 | 0.057 | 0.108 |
| 8 | 8 | 12 | 10 | 12 | 11 | 62.161 | 87.497 | 63.359 | 78.320 | 67.436 | 68.003 | 0.263 | 0.109 | 0.197 | 0.121 | 0.310 | 0.335 | 0.049 | 0.026 | 0.089 | 0.012 | 0.068 | 0.068 |
| 8 | 17 | 11 | 10 | 12 | 13 | 72.936 | 88.083 | 70.743 | 93.162 | 82.691 | 70.543 | 0.235 | 0.234 | 0.203 | 0.108 | 0.338 | 0.390 | 0.060 | 0.074 | 0.119 | 0.019 | 0.125 | 0.124 |
| 8 | 15 | 16 | 14 | 13 | 7 | 61.516 | 96.991 | 120.210 | 97.744 | 99.460 | 103.620 | 0.316 | 0.251 | 0.265 | 0.196 | 0.273 | 0.260 | 0.090 | 0.069 | 0.061 | 0.016 | 0.165 | 0.169 |
| 5 | 12 | 5 | 11 | 12 | 13 | 50.967 | 68.807 | 62.975 | 70.000 | 62.137 | 76.115 | 0.193 | 0.186 | 0.127 | 0.134 | 0.245 | 0.313 | 0.012 | 0.031 | 0.037 | 0.012 | 0.040 | 0.143 |
| 12 | 9 | 10 | 9 | 10 | 16 | 67.873 | 67.600 | 70.897 | 71.158 | 79.617 | 64.269 | 0.318 | 0.154 | 0.224 | 0.078 | 0.254 | 0.255 | 0.016 | 0.042 | 0.049 | 0.015 | 0.049 | 0.099 |
| 9 | 10 | 9 | 13 | 11 | 10 | 64.000 | 76.149 | 92.537 | 54.862 | 64.884 | 68.924 | 0.234 | 0.216 | 0.173 | 0.096 | 0.299 | 0.332 | 0.028 | 0.035 | 0.062 | 0.019 | 0.057 | 0.079 |
| 10 | 11 | 10 | 12 | 10 | 15 | 59.475 | 70.529 | 68.889 | 65.263 | 74.113 | 66.287 | 0.235 | 0.162 | 0.161 | 0.141 | 0.302 | 0.320 | 0.024 | 0.036 | 0.034 | 0.017 | 0.083 | 0.159 |
| 11 | 11 | 11 | 12 | 14 | 11 | 62.822 | 72.404 | 73.687 | 68.021 | 74.632 | 70.379 | 0.208 | 0.697 | 1.250 | 0.792 | 2.750 | 1.587 | 0.012 | 0.036 | 0.064 | 0.040 | 0.142 | 0.082 |
| 6 | 14 | 7 | 16 | 10 | 7 | 73.038 | 76.691 | 75.000 | 74.041 | 82.396 | 62.999 | 0.488 | 0.411 | 0.981 | 0.330 | 2.080 | 1.420 | 0.256 | 0.205 | 0.211 | 0.153 | 0.300 | 0.309 |


| Jn $=$ Job \#1 | MA $=$ Machine A |
| :--- | :--- |
| Jn $=$ Job \#2 | MB $=$ Machine B |
| Jn $=$ Job \#3 | MC $=$ Machine C |
| J = Job \#4 | MD $=$ Machine D |
| Jn $=$ Job \#5 | ME $=$ Machine E |
| Jn = Job \#6 | ME $=$ Machine F |

$\mathrm{Jn}=\mathrm{Job} \# 5 \quad \mathrm{MD}=$ Machine D
Jn = Job \#6 $\quad$ ME $=$ Machine F

Table 5-4 Simulation Results where Scheduling Rule = FIFO, Job Arrival = "Medium"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | $J 5$ | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 21 | 23 | 22 | 30 | 26 | 27 | 73.162 | 77.137 | 75.349 | 68.000 | 123.190 | 88.243 | 0.548 | 0.471 | 0.434 | 0.370 | 0.633 | 0.696 | 0.975 | 0.127 | 0.109 | 0.086 | 0.296 | 0.497 |
| 19 | 25 | 32 | 20 | 30 | 22 | 69.117 | 80.157 | 77.291 | 75.420 | 78.520 | 100.130 | 0.563 | 0.458 | 0.476 | 0.346 | 0.652 | 0.676 | 0.129 | 0.137 | 0.182 | 0.050 | 0.334 | 0.382 |
| 26 | 28 | 17 | 27 | 29 | 21 | 63.528 | 70.138 | 64.570 | 69.590 | 127.100 | 129.980 | 0.522 | 0.497 | 0.413 | 0.375 | 0.634 | 0.667 | 0.107 | 0.168 | 0.118 | 0.067 | 0.341 | 0.520 |
| 18 | 32 | 16 | 39 | 38 | 9 | 93.196 | 72.873 | 75.171 | 76.371 | 131.380 | 130.600 | 0.510 | 0.529 | 0.514 | 0.339 | 0.716 | 0.660 | 0.092 | 0.182 | 0.205 | 0.085 | 0.402 | 0.295 |
| 23 | 28 | 27 | 29 | 26 | 17 | 83.249 | 80.503 | 93.652 | 79.158 | 135.240 | 117.360 | 0.599 | 0.496 | 0.458 | 0.385 | 0.687 | 0.667 | 0.216 | 0.193 | 0.191 | 0.076 | 0.416 | 0.423 |
| 28 | 31 | 16 | 31 | 29 | 20 | 75.681 | 82.620 | 78.238 | 75.822 | 102.480 | 165.400 | 0.550 | 0.525 | 0.455 | 0.383 | 0.693 | 0.662 | 0.128 | 0.188 | 0.173 | 0.073 | 0.457 | 0.450 |
| 21 | 19 | 23 | 31 | 30 | 26 | 83.000 | 71.887 | 77.010 | 78.021 | 97.461 | 92.361 | 0.516 | 0.470 | 0.488 | 0.327 | 0.648 | 0.661 | 0.096 | 0.125 | 0.231 | 0.043 | 0.281 | 0.436 |
| 19 | 19 | 22 | 31 | 36 | 27 | 65.218 | 69.837 | 81.248 | 68.004 | 92.979 | 101.470 | 0.536 | 0.468 | 0.500 | 0.351 | 0.656 | 0.675 | 0.090 | 0.118 | 0.200 | 0.072 | 0.374 | 0.414 |
| 16 | 31 | 24 | 28 | 29 | 25 | 84.098 | 81.137 | 83.476 | 72.620 | 81.102 | 110.440 | 0.552 | 0.486 | 0.480 | 0.334 | 0.664 | 0.692 | 0.097 | 0.146 | 0.198 | 0.065 | 0.288 | 0.399 |
| 27 | 23 | 23 | 29 | 25 | 24 | 68.965 | 73.749 | 80.684 | 65.395 | 84.173 | 82.746 | 0.516 | 0.472 | 0.423 | 0.379 | 0.650 | 0.633 | 0.102 | 0.154 | 0.146 | 0.062 | 0.244 | 0.402 |
| 22 | 27 | 25 | 28 | 19 | 28 | 77.584 | 75.171 | 76.497 | 72.127 | 78.887 | 90.236 | 0.582 | 0.466 | 0.394 | 0.384 | 0.652 | 0.727 | 0.088 | 0.110 | 0.126 | 0.075 | 0.318 | 0.526 |
| 22 | 25 | 28 | 23 | 33 | 24 | 85.087 | 82.318 | 80.709 | 80.915 | 109.850 | 120.860 | 0.578 | 0.483 | 0.492 | 0.353 | 0.662 | 0.693 | 0.191 | 0.151 | 0.243 | 0.063 | 0.447 | 0.503 |
| 23 | 31 | 25 | 22 | 29 | 23 | 84.062 | 80.855 | 71.356 | 82.649 | 157.230 | 116.540 | 0.574 | 0.485 | 0.486 | 0.358 | 0.673 | 0.692 | 0.109 | 0.122 | 0.213 | 0.048 | 0.299 | 0.565 |
| 18 | 26 | 34 | 26 | 31 | 20 | 90.444 | 86.984 | 92.983 | 70.783 | 98.421 | 127.420 | 0.539 | 0.437 | 0.484 | 0.359 | 0.662 | 0.670 | 0.087 | 0.149 | 0.169 | 0.072 | 0.386 | 0.427 |
| 16 | 42 | 18 | 21 | 25 | 23 | 102.860 | 78.607 | 86.486 | 74.865 | 75.786 | 121.730 | 0.562 | 0.531 | 0.452 | 0.339 | 0.671 | 0.694 | 0.148 | 0.207 | 0.231 | 0.074 | 0.422 | 0.486 |
| 20 | 15 | 29 | 32 | 26 | 29 | 90.941 | 81.708 | 88.445 | 65.858 | 88.710 | 97.379 | 0.558 | 0.425 | 0.448 | 0.341 | 0.620 | 0.677 | 0.118 | 0.122 | 0.186 | 0.055 | 0.285 | 0.473 |
| 15 | 22 | 30 | 31 | 31 | 27 | 74.573 | 77.856 | 80.151 | 73.534 | 110.020 | 109.190 | 0.579 | 0.463 | 0.501 | 0.338 | 0.654 | 0.705 | 0.162 | 0.208 | 0.197 | 0.038 | 0.299 | 0.529 |
| 27 | 27 | 29 | 23 | 26 | 22 | 77.286 | 95.107 | 80.134 | 68.390 | 98.357 | 99.360 | 0.552 | 0.486 | 0.424 | 0.392 | 0.635 | 0.677 | 0.137 | 0.105 | 0.148 | 0.120 | 0.302 | 0.475 |
| 22 | 24 | 28 | 23 | 27 | 23 | 96.983 | 87.132 | 71.989 | 69.649 | 110.110 | 116.030 | 0.552 | 0.447 | 0.442 | 0.364 | 0.616 | 0.670 | 0.068 | 0.140 | 0.138 | 0.057 | 0.276 | 0.432 |
| 23 | 22 | 16 | 33 | 33 | 26 | 67.204 | 74.426 | 82.529 | 69.696 | 91.024 | 106.640 | 0.554 | 0.485 | 0.482 | 0.328 | 0.677 | 0.637 | 0.099 | 0.112 | 0.260 | 0.046 | 0.252 | 0.350 |


| Jn $=$ Job \#1 | MA $=$ Machine A |
| :--- | :--- |
| Jn $=$ Job \#2 | MB $=$ Machine B |
| Jn $=$ Job \#3 | MC $=$ Machine C |
| Jn $=$ Job \#4 | MD $=$ Machine D |
| Jn $=$ Job \#5 | ME $=$ Machine E |

$\mathrm{Jn}=\mathrm{Job}$ \#5 $\quad \mathrm{MD}=$ Machine D
Jn = Job \#6 ME = Machine F

Table 5-5 Simulation Results where Scheduling Rule = EDD, Job Arrival = "Medium"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 22 | 25 | 23 | 32 | 28 | 29 | 74.162 | 79.137 | 76.349 | 70.000 | 125.190 | 90.243 | 0.648 | 0.671 | 0.534 | 0.570 | 0.833 | 0.896 | 0.985 | 0.147 | 0.119 | 0.106 | 0.316 | 0.517 |
| 21 | 27 | 35 | 23 | 31 | 23 | 72.117 | 83.157 | 79.291 | 77.420 | 79.520 | 101.130 | 0.863 | 0.758 | 0.676 | 0.546 | 0.752 | 0.776 | 0.159 | 0.167 | 0.202 | 0.070 | 0.344 | 0.392 |
| 29 | 30 | 20 | 28 | 31 | 22 | 66.528 | 71.138 | 67.570 | 71.590 | 129.100 | 130.980 | 0.822 | 0.597 | 0.713 | 0.575 | 0.834 | 0.767 | 0.137 | 0.178 | 0.148 | 0.087 | 0.361 | 0.530 |
| 19 | 35 | 16 | 42 | 38 | 9 | 93.196 | 75.873 | 76.171 | 79.371 | 131.380 | 130.600 | 0.510 | 0.829 | 0.614 | 0.639 | 0.716 | 0.660 | 0.092 | 0.212 | 0.215 | 0.115 | 0.402 | 0.295 |
| 25 | 31 | 29 | 30 | 28 | 17 | 85.249 | 81.503 | 95.652 | 82.158 | 137.240 | 117.360 | 0.799 | 0.596 | 0.658 | 0.685 | 0.887 | 0.667 | 0.236 | 0.203 | 0.211 | 0.106 | 0.436 | 0.423 |
| 30 | 31 | 19 | 32 | 30 | 20 | 78.681 | 83.620 | 80.238 | 75.822 | 103.480 | 165.400 | 0.850 | 0.625 | 0.655 | 0.383 | 0.793 | 0.662 | 0.158 | 0.198 | 0.193 | 0.073 | 0.467 | 0.450 |
| 24 | 19 | 24 | 33 | 31 | 26 | 84.000 | 73.887 | 80.010 | 78.021 | 98.461 | 92.361 | 0.616 | 0.670 | 0.788 | 0.327 | 0.748 | 0.661 | 0.106 | 0.145 | 0.261 | 0.043 | 0.291 | 0.436 |
| 22 | 22 | 23 | 33 | 37 | 27 | 66.218 | 71.837 | 84.248 | 71.004 | 93.979 | 101.470 | 0.636 | 0.668 | 0.800 | 0.651 | 0.756 | 0.675 | 0.100 | 0.138 | 0.230 | 0.102 | 0.384 | 0.414 |
| 17 | 32 | 26 | 30 | 32 | 28 | 86.098 | 83.137 | 84.476 | 73.620 | 84.102 | 113.440 | 0.752 | 0.686 | 0.580 | 0.434 | 0.964 | 0.992 | 0.117 | 0.166 | 0.208 | 0.075 | 0.318 | 0.429 |
| 30 | 24 | 25 | 29 | 25 | 25 | 70.965 | 73.749 | 83.684 | 66.395 | 84.173 | 83.746 | 0.716 | 0.472 | 0.723 | 0.479 | 0.650 | 0.733 | 0.122 | 0.154 | 0.176 | 0.072 | 0.244 | 0.412 |
| 22 | 30 | 25 | 28 | 19 | 28 | 77.584 | 75.171 | 76.497 | 75.127 | 78.887 | 90.236 | 0.582 | 0.466 | 0.394 | 0.684 | 0.652 | 0.727 | 0.088 | 0.110 | 0.126 | 0.105 | 0.318 | 0.526 |
| 23 | 27 | 29 | 26 | 33 | 24 | 86.087 | 85.318 | 81.709 | 82.915 | 109.850 | 120.860 | 0.678 | 0.783 | 0.592 | 0.553 | 0.662 | 0.693 | 0.201 | 0.181 | 0.253 | 0.083 | 0.447 | 0.503 |
| 25 | 33 | 28 | 23 | 30 | 23 | 87.062 | 81.855 | 73.356 | 84.649 | 158.230 | 116.540 | 0.874 | 0.585 | 0.686 | 0.558 | 0.773 | 0.692 | 0.139 | 0.132 | 0.233 | 0.068 | 0.309 | 0.565 |
| 18 | 26 | 34 | 26 | 34 | 23 | 90.444 | 86.984 | 92.983 | 70.783 | 101.421 | 130.420 | 0.539 | 0.437 | 0.484 | 0.359 | 0.962 | 0.970 | 0.087 | 0.149 | 0.169 | 0.072 | 0.416 | 0.457 |
| 19 | 43 | 20 | 22 | 27 | 24 | 104.860 | 79.607 | 89.486 | 75.865 | 77.786 | 122.730 | 0.762 | 0.631 | 0.752 | 0.439 | 0.871 | 0.794 | 0.168 | 0.217 | 0.261 | 0.084 | 0.442 | 0.496 |
| 20 | 18 | 29 | 34 | 28 | 32 | 90.941 | 83.708 | 88.445 | 68.858 | 90.710 | 100.379 | 0.558 | 0.625 | 0.448 | 0.641 | 0.820 | 0.977 | 0.118 | 0.142 | 0.186 | 0.085 | 0.305 | 0.503 |
| 16 | 24 | 31 | 31 | 31 | 27 | 75.573 | 77.856 | 81.151 | 75.534 | 110.020 | 109.190 | 0.679 | 0.463 | 0.601 | 0.538 | 0.654 | 0.705 | 0.172 | 0.208 | 0.207 | 0.058 | 0.299 | 0.529 |
| 29 | 29 | 32 | 26 | 28 | 25 | 80.286 | 98.107 | 82.134 | 70.390 | 100.357 | 102.360 | 0.852 | 0.786 | 0.624 | 0.592 | 0.835 | 0.977 | 0.167 | 0.135 | 0.168 | 0.140 | 0.322 | 0.505 |
| 22 | 24 | 31 | 24 | 29 | 24 | 99.983 | 88.132 | 71.989 | 69.649 | 112.110 | 117.030 | 0.852 | 0.547 | 0.442 | 0.364 | 0.816 | 0.770 | 0.098 | 0.150 | 0.138 | 0.057 | 0.296 | 0.442 |
| 23 | 22 | 16 | 33 | 33 | 26 | 67.204 | 74.426 | 82.529 | 69.696 | 91.024 | 106.640 | 0.554 | 0.485 | 0.482 | 0.328 | 0.677 | 0.637 | 0.099 | 0.112 | 0.260 | 0.046 | 0.252 | 0.350 |

Jn = Job \#1
$\begin{array}{ll}\mathrm{Jn}=\mathrm{Job} \# 2 & \text { MA }=\text { Machine A } \\ \text { MB }=\text { Machine B }\end{array}$
$\mathrm{Jn}=\mathrm{Job} \# 3 \quad \mathrm{MC}=$ Machine C
$\begin{array}{ll}\mathrm{Jn}=\text { Job \#4 } & \text { MD }=\text { Machine D } \\ \text { Jn }=\text { Job } \# 5 & \text { ME }\end{array}$
$\begin{array}{ll}\mathrm{Jn}=\mathrm{Job} \text { \#5 } & \text { ME }=\text { Machine E } \\ \mathrm{Jn}=\text { Job \#6 } & \text { ME }=\text { Machine F }\end{array}$

Table 5-6 Simulation Results where Scheduling Rule = SPT, Job Arrival = "Medium"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 20 | 21 | 21 | 28 | 24 | 25 | 72.162 | 75.137 | 74.349 | 66.000 | 121.190 | 86.243 | 0.448 | 0.271 | 0.334 | 0.170 | 0.433 | 0.496 | 0.965 | 0.107 | 0.099 | 0.066 | 0.276 | 0.477 |
| 17 | 23 | 29 | 17 | 29 | 21 | 66.117 | 77.157 | 75.291 | 73.420 | 77.520 | 99.130 | 0.263 | 0.158 | 0.276 | 0.146 | 0.552 | 0.576 | 0.099 | 0.107 | 0.162 | 0.030 | 0.324 | 0.372 |
| 23 | 26 | 14 | 26 | 27 | 20 | 60.528 | 69.138 | 61.570 | 67.590 | 125.100 | 128.980 | 0.222 | 0.397 | 0.113 | 0.175 | 0.434 | 0.567 | 0.077 | 0.158 | 0.088 | 0.047 | 0.321 | 0.510 |
| 17 | 29 | 16 | 36 | 38 | 9 | 93.196 | 69.873 | 74.171 | 73.371 | 131.380 | 130.600 | 0.510 | 0.229 | 0.414 | 0.039 | 0.716 | 0.660 | 0.092 | 0.152 | 0.195 | 0.055 | 0.402 | 0.295 |
| 21 | 25 | 25 | 28 | 24 | 17 | 81.249 | 79.503 | 91.652 | 76.158 | 133.240 | 117.360 | 0.399 | 0.396 | 0.258 | 0.085 | 0.487 | 0.667 | 0.196 | 0.183 | 0.171 | 0.046 | 0.396 | 0.423 |
| 26 | 31 | 13 | 30 | 28 | 20 | 72.681 | 81.620 | 76.238 | 75.822 | 101.480 | 165.400 | 0.250 | 0.425 | 0.255 | 0.383 | 0.593 | 0.662 | 0.098 | 0.178 | 0.153 | 0.073 | 0.447 | 0.450 |
| 18 | 19 | 22 | 29 | 29 | 26 | 82.000 | 69.887 | 74.010 | 78.021 | 96.461 | 92.361 | 0.416 | 0.270 | 0.188 | 0.327 | 0.548 | 0.661 | 0.086 | 0.105 | 0.201 | 0.043 | 0.271 | 0.436 |
| 16 | 16 | 21 | 29 | 35 | 27 | 64.218 | 67.837 | 78.248 | 65.004 | 91.979 | 101.470 | 0.436 | 0.268 | 0.200 | 0.051 | 0.556 | 0.675 | 0.080 | 0.098 | 0.170 | 0.042 | 0.364 | 0.414 |
| 15 | 30 | 22 | 26 | 26 | 22 | 82.098 | 79.137 | 82.476 | 71.620 | 78.102 | 107.440 | 0.352 | 0.286 | 0.380 | 0.234 | 0.364 | 0.392 | 0.077 | 0.126 | 0.188 | 0.055 | 0.258 | 0.369 |
| 24 | 22 | 21 | 29 | 25 | 23 | 66.965 | 73.749 | 77.684 | 64.395 | 84.173 | 81.746 | 0.316 | 0.472 | 0.123 | 0.279 | 0.650 | 0.533 | 0.082 | 0.154 | 0.116 | 0.052 | 0.244 | 0.392 |
| 22 | 24 | 25 | 28 | 19 | 28 | 77.584 | 75.171 | 76.497 | 69.127 | 78.887 | 90.236 | 0.582 | 0.466 | 0.394 | 0.084 | 0.652 | 0.727 | 0.088 | 0.110 | 0.126 | 0.045 | 0.318 | 0.526 |
| 21 | 23 | 27 | 20 | 33 | 24 | 84.087 | 79.318 | 79.709 | 78.915 | 109.850 | 120.860 | 0.478 | 0.183 | 0.392 | 0.153 | 0.662 | 0.693 | 0.181 | 0.121 | 0.233 | 0.043 | 0.447 | 0.503 |
| 21 | 29 | 22 | 21 | 28 | 23 | 81.062 | 79.855 | 69.356 | 80.649 | 156.230 | 116.540 | 0.274 | 0.385 | 0.286 | 0.158 | 0.573 | 0.692 | 0.079 | 0.112 | 0.193 | 0.028 | 0.289 | 0.565 |
| 18 | 26 | 34 | 26 | 28 | 17 | 90.444 | 86.984 | 92.983 | 70.783 | 95.421 | 124.420 | 0.539 | 0.437 | 0.484 | 0.359 | 0.362 | 0.370 | 0.087 | 0.149 | 0.169 | 0.072 | 0.356 | 0.397 |
| 13 | 41 | 16 | 20 | 23 | 22 | 100.860 | 77.607 | 83.486 | 73.865 | 73.786 | 120.730 | 0.362 | 0.431 | 0.152 | 0.239 | 0.471 | 0.594 | 0.128 | 0.197 | 0.201 | 0.064 | 0.402 | 0.476 |
| 20 | 12 | 29 | 30 | 24 | 26 | 90.941 | 79.708 | 88.445 | 62.858 | 86.710 | 94.379 | 0.558 | 0.225 | 0.448 | 0.041 | 0.420 | 0.377 | 0.118 | 0.102 | 0.186 | 0.025 | 0.265 | 0.443 |
| 14 | 20 | 29 | 31 | 31 | 27 | 73.573 | 77.856 | 79.151 | 71.534 | 110.020 | 109.190 | 0.479 | 0.463 | 0.401 | 0.138 | 0.654 | 0.705 | 0.152 | 0.208 | 0.187 | 0.018 | 0.299 | 0.529 |
| 25 | 25 | 26 | 20 | 24 | 19 | 74.286 | 92.107 | 78.134 | 66.390 | 96.357 | 96.360 | 0.252 | 0.186 | 0.224 | 0.192 | 0.435 | 0.377 | 0.107 | 0.075 | 0.128 | 0.100 | 0.282 | 0.445 |
| 22 | 24 | 25 | 22 | 25 | 22 | 93.983 | 86.132 | 71.989 | 69.649 | 108.110 | 115.030 | 0.252 | 0.347 | 0.442 | 0.364 | 0.416 | 0.570 | 0.038 | 0.130 | 0.138 | 0.057 | 0.256 | 0.422 |
| 23 | 22 | 16 | 33 | 33 | 26 | 67.204 | 74.426 | 82.529 | 69.696 | 91.024 | 106.640 | 0.554 | 0.485 | 0.482 | 0.328 | 0.677 | 0.637 | 0.099 | 0.112 | 0.260 | 0.046 | 0.252 | 0.350 |


| Jn $=$ Job \#1 | MA $=$ Machine A |
| :--- | :--- |
| Jn $=$ Job \#2 | MB $=$ Machine B |
| Jn $=$ Job \#3 | MC $=$ Machine C |
| Jn $=$ Job \#4 | MD $=$ Machine D |
| Jn $=$ Job \#5 | ME $=$ Machine E |

$\begin{array}{ll}\mathrm{Jn}=\mathrm{Job} \text { \#4 } & \mathrm{MC}=\text { Machine C } \\ \mathrm{Jn}=\mathrm{Job} \# 5 & \text { MD }=\text { Machine D }\end{array}$
Jn = Job \#6 $\quad$ ME $=$ Machine $F$

Table 5-7 Simulation Results where Scheduling Rule = FIFO, Job Arrival $=$ "High"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | $J 5$ | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 35 | 36 | 31 | 40 | 33 | 30 | 722.540 | 641.800 | 685.320 | 729.620 | 648.610 | 635.690 | 0.999 | 0.791 | 0.704 | 0.639 | 1.000 | 1.000 | 5.800 | 1.660 | 1.010 | 0.424 | 37.335 | 34.225 |
| 30 | 32 | 41 | 29 | 44 | 31 | 617.520 | 707.920 | 639.650 | 690.580 | 718.330 | 627.130 | 0.992 | 0.768 | 0.714 | 0.599 | 1.000 | 1.000 | 0.431 | 33.461 | 7.139 | 34.148 | 1.065 | 1.224 |
| 40 | 36 | 20 | 36 | 35 | 34 | 718.910 | 665.300 | 660.960 | 736.940 | 652.920 | 693.080 | 0.997 | 0.771 | 0.697 | 0.667 | 1.000 | 1.000 | 0.590 | 35.663 | 7.995 | 37.049 | 0.883 | 1.083 |
| 21 | 35 | 20 | 40 | 36 | 14 | 631.830 | 740.750 | 648.650 | 748.530 | 736.880 | 648.480 | 0.998 | 0.823 | 0.786 | 0.592 | 1.000 | 1.000 | 0.516 | 48.710 | 3.916 | 28.063 | 2.053 | 1.481 |
| 38 | 39 | 32 | 42 | 34 | 30 | 723.540 | 643.800 | 688.320 | 732.620 | 649.610 | 635.690 | 1.000 | 0.991 | 1.000 | 0.939 | 1.000 | 1.000 | 5.810 | 1.680 | 1.040 | 0.454 | 37.345 | 34.225 |
| 31 | 33 | 43 | 31 | 47 | 34 | 619.520 | 709.920 | 640.650 | 691.580 | 721.330 | 630.130 | 1.000 | 0.968 | 0.814 | 0.699 | 1.000 | 1.000 | 0.451 | 33.481 | 7.149 | 34.158 | 1.095 | 1.254 |
| 43 | 37 | 22 | 36 | 35 | 35 | 720.910 | 665.300 | 663.960 | 737.940 | 652.920 | 694.080 | 1.000 | 0.771 | 0.997 | 0.767 | 1.000 | 1.000 | 0.610 | 35.663 | 8.025 | 37.059 | 0.883 | 1.093 |
| 21 | 38 | 20 | 40 | 36 | 14 | 631.830 | 740.750 | 648.650 | 751.530 | 736.880 | 648.480 | 0.998 | 0.823 | 0.786 | 0.892 | 1.000 | 1.000 | 0.516 | 48.710 | 3.916 | 28.093 | 2.053 | 1.481 |
| 39 | 41 | 33 | 45 | 34 | 30 | 724.540 | 646.800 | 689.320 | 734.620 | 649.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.139 | 1.000 | 1.000 | 5.820 | 1.710 | 1.050 | 0.474 | 37.345 | 34.225 |
| 43 | 39 | 21 | 38 | 36 | 34 | 719.910 | 667.300 | 663.960 | 739.940 | 653.920 | 693.080 | 1.000 | 0.971 | 0.997 | 0.967 | 1.000 | 1.000 | 0.600 | 35.683 | 8.025 | 37.079 | 0.893 | 1.083 |
| 22 | 36 | 22 | 42 | 39 | 17 | 633.830 | 742.750 | 649.650 | 749.530 | 739.880 | 651.480 | 1.000 | 1.000 | 0.886 | 0.692 | 1.000 | 1.000 | 0.536 | 48.730 | 3.926 | 28.073 | 2.083 | 1.511 |
| 41 | 40 | 34 | 42 | 34 | 31 | 725.540 | 643.800 | 691.320 | 733.620 | 649.610 | 636.690 | 1.000 | 0.991 | 1.000 | 1.039 | 1.000 | 1.000 | 5.830 | 1.680 | 1.070 | 0.464 | 37.345 | 34.235 |
| 31 | 36 | 43 | 31 | 47 | 34 | 619.520 | 709.920 | 640.650 | 694.580 | 721.330 | 630.130 | 1.000 | 0.968 | 0.814 | 0.999 | 1.000 | 1.000 | 0.451 | 33.481 | 7.149 | 34.188 | 1.095 | 1.254 |
| 42 | 36 | 23 | 37 | 36 | 34 | 721.910 | 666.300 | 662.960 | 736.940 | 653.920 | 693.080 | 1.000 | 0.871 | 0.897 | 0.667 | 1.000 | 1.000 | 0.620 | 35.673 | 8.015 | 37.049 | 0.893 | 1.083 |
| 24 | 35 | 21 | 42 | 37 | 14 | 632.830 | 742.750 | 651.650 | 748.530 | 737.880 | 648.480 | 1.000 | 1.000 | 1.000 | 0.592 | 1.000 | 1.000 | 0.526 | 48.730 | 3.946 | 28.063 | 2.063 | 1.481 |
| 41 | 42 | 33 | 44 | 35 | 30 | 724.540 | 645.800 | 691.320 | 735.620 | 650.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.820 | 1.700 | 1.070 | 0.484 | 37.355 | 34.225 |
| 32 | 34 | 45 | 33 | 50 | 37 | 621.520 | 711.920 | 641.650 | 692.580 | 724.330 | 633.130 | 1.000 | 1.000 | 0.914 | 0.799 | 1.000 | 1.000 | 0.471 | 33.501 | 7.159 | 34.168 | 1.125 | 1.284 |
| 46 | 38 | 24 | 36 | 35 | 36 | 722.910 | 665.300 | 666.960 | 738.940 | 652.920 | 695.080 | 1.000 | 0.771 | 1.000 | 0.867 | 1.000 | 1.000 | 0.630 | 35.663 | 8.055 | 37.069 | 0.883 | 1.103 |
| 21 | 41 | 20 | 40 | 36 | 14 | 631.830 | 740.750 | 648.650 | 754.530 | 736.880 | 648.480 | 0.998 | 0.823 | 0.786 | 1.000 | 1.000 | 1.000 | 0.516 | 48.710 | 3.916 | 28.123 | 2.053 | 1.481 |
| 40 | 44 | 33 | 48 | 34 | 30 | 724.540 | 649.800 | 690.320 | 737.620 | 649.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.820 | 1.740 | 1.060 | 0.504 | 37.345 | 34.225 |

$\mathrm{Jn}=\mathrm{Job} \# 1$
$\mathrm{Jn}=\mathrm{Job} \# 2$
$\mathrm{Jn}=\mathrm{Job} \# 3$
$\mathrm{Jn}=\mathrm{Job} \# 4$
$\mathrm{Jn}=\mathrm{Job} \# 5$
$\mathrm{Jn}=\mathrm{Job}$ \#6

MA = Machine A
MB = Machine B
MC = Machine C
MD = Machine D
ME $=$ Machine E
ME $=$ Machine F

Table 5-8 Simulation Results where Scheduling Rule = EDD, Job Arrival = "High"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 36 | 39 | 31 | 43 | 33 | 30 | 722.540 | 644.800 | 686.320 | 732.620 | 648.610 | 635.690 | 0.999 | 1.000 | 0.804 | 0.939 | 1.000 | 1.000 | 5.800 | 1.690 | 1.020 | 0.454 | 37.335 | 34.225 |
| 32 | 35 | 43 | 30 | 46 | 31 | 619.520 | 708.920 | 641.650 | 693.580 | 720.330 | 627.130 | 1.000 | 0.868 | 0.914 | 0.899 | 1.000 | 1.000 | 0.451 | 33.471 | 7.159 | 34.178 | 1.085 | 1.224 |
| 42 | 36 | 23 | 37 | 36 | 34 | 721.910 | 666.300 | 662.960 | 736.940 | 653.920 | 693.080 | 1.000 | 0.871 | 0.897 | 0.667 | 1.000 | 1.000 | 0.620 | 35.673 | 8.015 | 37.049 | 0.893 | 1.083 |
| 24 | 35 | 21 | 42 | 37 | 14 | 632.830 | 742.750 | 651.650 | 748.530 | 737.880 | 648.480 | 1.000 | 1.000 | 1.000 | 0.592 | 1.000 | 1.000 | 0.526 | 48.730 | 3.946 | 28.063 | 2.063 | 1.481 |
| 41 | 42 | 33 | 44 | 35 | 30 | 724.540 | 645.800 | 691.320 | 735.620 | 650.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.820 | 1.700 | 1.070 | 0.484 | 37.355 | 34.225 |
| 32 | 34 | 45 | 33 | 50 | 37 | 621.520 | 711.920 | 641.650 | 692.580 | 724.330 | 633.130 | 1.000 | 1.000 | 0.914 | 0.799 | 1.000 | 1.000 | 0.471 | 33.501 | 7.159 | 34.168 | 1.125 | 1.284 |
| 46 | 38 | 24 | 36 | 35 | 36 | 722.910 | 665.300 | 666.960 | 738.940 | 652.920 | 695.080 | 1.000 | 0.771 | 1.000 | 0.867 | 1.000 | 1.000 | 0.630 | 35.663 | 8.055 | 37.069 | 0.883 | 1.103 |
| 21 | 41 | 20 | 40 | 36 | 14 | 631.830 | 740.750 | 648.650 | 754.530 | 736.880 | 648.480 | 0.998 | 0.823 | 0.786 | 1.000 | 1.000 | 1.000 | 0.516 | 48.710 | 3.916 | 28.123 | 2.053 | 1.481 |
| 40 | 44 | 33 | 48 | 34 | 30 | 724.540 | 649.800 | 690.320 | 737.620 | 649.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.820 | 1.740 | 1.060 | 0.504 | 37.345 | 34.225 |
| 45 | 42 | 23 | 39 | 38 | 34 | 721.910 | 668.300 | 665.960 | 742.940 | 655.920 | 693.080 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.620 | 35.693 | 8.045 | 37.109 | 0.913 | 1.083 |
| 24 | 36 | 25 | 43 | 40 | 17 | 636.830 | 743.750 | 651.650 | 749.530 | 740.880 | 651.480 | 1.000 | 1.000 | 1.000 | 0.692 | 1.000 | 1.000 | 0.566 | 48.740 | 3.946 | 28.073 | 2.093 | 1.511 |
| 44 | 40 | 35 | 44 | 35 | 31 | 726.540 | 645.800 | 694.320 | 733.620 | 650.610 | 636.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.840 | 1.700 | 1.100 | 0.464 | 37.355 | 34.235 |
| 34 | 39 | 44 | 33 | 48 | 34 | 620.520 | 711.920 | 643.650 | 697.580 | 722.330 | 630.130 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.461 | 33.501 | 7.179 | 34.218 | 1.105 | 1.254 |
| 43 | 37 | 25 | 39 | 39 | 37 | 723.910 | 668.300 | 663.960 | 737.940 | 656.920 | 696.080 | 1.000 | 1.000 | 0.997 | 0.767 | 1.000 | 1.000 | 0.640 | 35.693 | 8.025 | 37.059 | 0.923 | 1.113 |
| 27 | 36 | 23 | 42 | 37 | 15 | 634.830 | 742.750 | 654.650 | 749.530 | 737.880 | 649.480 | 1.000 | 1.000 | 1.000 | 0.692 | 1.000 | 1.000 | 0.546 | 48.730 | 3.976 | 28.073 | 2.063 | 1.491 |
| 41 | 45 | 33 | 44 | 35 | 30 | 724.540 | 645.800 | 691.320 | 738.620 | 650.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.820 | 1.700 | 1.070 | 0.514 | 37.355 | 34.225 |
| 33 | 36 | 46 | 36 | 50 | 37 | 622.520 | 714.920 | 642.650 | 694.580 | 724.330 | 633.130 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 | 1.000 | 0.481 | 33.531 | 7.169 | 34.188 | 1.125 | 1.284 |
| 48 | 40 | 27 | 37 | 36 | 36 | 725.910 | 666.300 | 668.960 | 740.940 | 653.920 | 695.080 | 1.000 | 0.871 | 1.000 | 1.000 | 1.000 | 1.000 | 0.660 | 35.673 | 8.075 | 37.089 | 0.893 | 1.103 |
| 22 | 43 | 21 | 43 | 36 | 14 | 632.830 | 743.750 | 649.650 | 756.530 | 736.880 | 648.480 | 1.000 | 1.000 | 0.886 | 1.000 | 1.000 | 1.000 | 0.526 | 48.740 | 3.926 | 28.143 | 2.053 | 1.481 |
| 42 | 46 | 36 | 49 | 35 | 30 | 727.540 | 650.800 | 692.320 | 739.620 | 650.610 | 635.690 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 5.850 | 1.750 | 1.080 | 0.524 | 37.355 | 34.225 |

$\mathrm{Jn}=\mathrm{Job} \# 1 \quad \mathrm{MA}=$ Machine A
$\mathrm{Jn}=\mathrm{Job} \# 2 \quad \mathrm{MB}=$ Machine B
$\mathrm{Jn}=\mathrm{Job} \# 3 \quad \mathrm{MC}=$ Machine C
Jn = Job \#4 $\quad$ MD $=$ Machine D
$\begin{array}{ll}\mathrm{Jn}=\mathrm{Job} \text { \#5 } & \text { ME }=\text { Machine E } \\ \mathrm{Jn}=\text { Job \#6 } & \text { ME }=\text { Machine F }\end{array}$
= Job \#6

Table 5-9 Simulation Results where Scheduling Rule = SPT, Job Arrival = "High"

| Num of Completed jobs (Parts) |  |  |  |  |  | Maximum Flowtime (Time Unit) |  |  |  |  |  | Average Machine Utilization (\%) |  |  |  |  |  | Average Job Q length for the machine (Parts) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| 34 | 33 | 31 | 37 | 33 | 30 | 722.540 | 638.800 | 684.320 | 726.620 | 648.610 | 635.690 | 0.999 | 0.491 | 0.604 | 0.339 | 1.000 | 1.000 | 5.800 | 1.630 | 1.000 | 0.394 | 37.335 | 34.225 |
| 28 | 29 | 39 | 28 | 42 | 31 | 615.520 | 706.920 | 637.650 | 687.580 | 716.330 | 627.130 | 0.792 | 0.668 | 0.514 | 0.299 | 0.800 | 1.000 | 0.411 | 33.451 | 7.119 | 34.118 | 1.045 | 1.224 |
| 38 | 36 | 17 | 35 | 34 | 34 | 715.910 | 664.300 | 658.960 | 736.940 | 651.920 | 693.080 | 0.697 | 0.671 | 0.497 | 0.667 | 0.900 | 1.000 | 0.560 | 35.653 | 7.975 | 37.049 | 0.873 | 1.083 |
| 18 | 35 | 19 | 38 | 35 | 14 | 630.830 | 738.750 | 645.650 | 748.530 | 735.880 | 648.480 | 0.898 | 0.623 | 0.486 | 0.592 | 0.900 | 1.000 | 0.506 | 48.690 | 3.886 | 28.063 | 2.043 | 1.481 |
| 35 | 36 | 31 | 40 | 33 | 30 | 722.540 | 641.800 | 685.320 | 729.620 | 648.610 | 635.690 | 0.900 | 0.791 | 0.700 | 0.639 | 0.900 | 1.000 | 5.800 | 1.660 | 1.010 | 0.424 | 37.335 | 34.225 |
| 30 | 32 | 41 | 29 | 44 | 31 | 617.520 | 707.920 | 639.650 | 690.580 | 718.330 | 627.130 | 0.800 | 0.768 | 0.714 | 0.599 | 0.700 | 0.700 | 0.431 | 33.461 | 7.139 | 34.148 | 1.065 | 1.224 |
| 40 | 36 | 20 | 36 | 35 | 34 | 718.910 | 665.300 | 660.960 | 736.940 | 652.920 | 693.080 | 0.800 | 0.771 | 0.697 | 0.667 | 1.000 | 0.900 | 0.590 | 35.663 | 7.995 | 37.049 | 0.883 | 1.083 |
| 21 | 35 | 20 | 40 | 36 | 14 | 631.830 | 740.750 | 648.650 | 748.530 | 736.880 | 648.480 | 0.998 | 0.823 | 0.786 | 0.592 | 1.000 | 1.000 | 0.516 | 48.710 | 3.916 | 28.063 | 2.053 | 1.481 |
| 38 | 38 | 33 | 42 | 34 | 30 | 724.540 | 643.800 | 688.320 | 731.620 | 649.610 | 635.690 | 1.000 | 0.700 | 0.900 | 0.839 | 1.000 | 1.000 | 5.820 | 1.680 | 1.040 | 0.444 | 37.345 | 34.225 |
| 41 | 36 | 19 | 37 | 34 | 34 | 717.910 | 666.300 | 661.960 | 736.940 | 651.920 | 693.080 | 0.800 | 0.871 | 0.797 | 0.667 | 0.800 | 1.000 | 0.580 | 35.673 | 8.005 | 37.049 | 0.873 | 1.083 |
| 20 | 36 | 19 | 41 | 38 | 17 | 630.830 | 741.750 | 647.650 | 749.530 | 738.880 | 651.480 | 0.700 | 0.900 | 0.686 | 0.692 | 1.000 | 1.000 | 0.506 | 48.720 | 3.906 | 28.073 | 2.073 | 1.511 |
| 38 | 40 | 33 | 40 | 33 | 31 | 724.540 | 641.800 | 688.320 | 733.620 | 648.610 | 636.690 | 1.000 | 0.791 | 0.700 | 1.000 | 0.900 | 1.000 | 5.820 | 1.660 | 1.040 | 0.464 | 37.335 | 34.235 |
| 28 | 33 | 42 | 29 | 46 | 34 | 618.520 | 707.920 | 637.650 | 691.580 | 720.330 | 630.130 | 0.900 | 0.768 | 0.514 | 0.699 | 0.900 | 1.000 | 0.441 | 33.461 | 7.119 | 34.158 | 1.085 | 1.254 |
| 41 | 35 | 21 | 35 | 33 | 31 | 719.910 | 664.300 | 661.960 | 735.940 | 650.920 | 690.080 | 1.000 | 0.671 | 0.797 | 0.567 | 0.700 | 0.700 | 0.600 | 35.653 | 8.005 | 37.039 | 0.863 | 1.053 |
| 21 | 34 | 19 | 42 | 37 | 13 | 630.830 | 742.750 | 648.650 | 747.530 | 737.880 | 647.480 | 0.800 | 1.000 | 0.700 | 0.492 | 1.000 | 0.900 | 0.506 | 48.730 | 3.916 | 28.053 | 2.063 | 1.471 |
| 41 | 39 | 33 | 44 | 35 | 30 | 724.540 | 645.800 | 691.320 | 732.620 | 650.610 | 635.690 | 1.000 | 1.000 | 1.000 | 0.700 | 1.000 | 1.000 | 5.820 | 1.700 | 1.070 | 0.454 | 37.355 | 34.225 |
| 31 | 32 | 44 | 30 | 50 | 37 | 620.520 | 708.920 | 640.650 | 690.580 | 724.330 | 633.130 | 1.000 | 0.700 | 0.814 | 0.599 | 1.000 | 1.000 | 0.461 | 33.471 | 7.149 | 34.148 | 1.125 | 1.284 |
| 44 | 36 | 21 | 35 | 34 | 36 | 719.910 | 664.300 | 664.960 | 736.940 | 651.920 | 695.080 | 0.700 | 0.671 | 1.000 | 0.667 | 0.900 | 1.000 | 0.600 | 35.653 | 8.035 | 37.049 | 0.873 | 1.103 |
| 20 | 39 | 19 | 37 | 36 | 14 | 630.830 | 737.750 | 647.650 | 752.530 | 736.880 | 648.480 | 0.898 | 0.523 | 0.686 | 0.800 | 1.000 | 1.000 | 0.506 | 48.680 | 3.906 | 28.103 | 2.053 | 1.481 |
| 38 | 42 | 30 | 47 | 33 | 30 | 721.540 | 648.800 | 688.320 | 735.620 | 648.610 | 635.690 | 0.700 | 1.000 | 0.800 | 1.000 | 0.900 | 1.000 | 5.790 | 1.730 | 1.040 | 0.484 | 37.335 | 34.225 |

Jn = Job \#1
$\mathrm{Jn}=\mathrm{Job} \# 2$ $\mathrm{Jn}=\mathrm{Job} \# 3$ $\mathrm{Jn}=\mathrm{Job} \# 4$
$\mathrm{In}=\mathrm{Job} \# 5$ $\mathrm{Jn}=\mathrm{Job}$ \#5
$\mathrm{Jn}=\mathrm{Job} \# 6$

MA = Machine A
$\mathrm{MB}=$ Machine B
$\mathrm{MC}=$ Machine C
MC = Machine C
MD = Machine D
ME $=$ Machine F

### 5.2.1 Parameter used in the BP-MLP

Table 5-10 Training Parameters .

| Parameter | Value |
| :--- | :--- |
| Number of sample | 180 |
| Network structure | $36-37-24$ |
| Stop Condition |  |
| Maximum Training times | 10000 |
| • Error | 0.01 |
| Learning Rate | 0.1 |

### 5.2.2 The Training Convergent Curve

The Mean Absolute Error (MAE) training convergent curve of the whole training process is shown in Figure 5-1. According to the curve, it can be seen that the slope decreases significantly prior to 150 training epoch.


Figure 5-1: Mean Absolute Error Convergent curve of Training

## 5-3 Comparison Between Simulation Results and Predict Results

Comparison between the results from ARENA simulation and the ANN scheduling model are summarized in Tables 5.11 to 5.14 . Note that only samples of results are included in the tables.

Table 5.11 Comparison of Number Completed Jobs.

| Sched. Rule | Job Arrival | ARENA SIMULATION RESULTS |  |  |  |  |  | ANN MODEL |  |  |  |  |  | DIFFERENCE (\%) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 |
| FIFO | Low | 12 | 17 | 14 | 15 | 12 | 11 | 15 | 66 | 31 | 48 | 46 | 31 | 0.20 | 0.74 | 0.55 | 0.69 | 0.74 | 0.65 |
| FIFO | Low | 12 | 12 | 10 | 11 | 12 | 19 | 43 | 63 | 20 | 59 | 23 | 21 | 0.72 | 0.81 | 0.50 | 0.81 | 0.48 | 0.10 |
| FIFO | Low | 11 | 11 | 14 | 13 | 16 | 12 | 41 | 45 | 36 | 49 | 40 | 37 | 0.73 | 0.76 | 0.61 | 0.73 | 0.60 | 0.68 |
| EDD | Low | 15 | 20 | 15 | 14 | 22 | 17 | 40 | 74 | 25 | 49 | 47 | 20 | 0.63 | 0.73 | 0.40 | 0.71 | 0.53 | 0.15 |
| EDD | Low | 13 | 14 | 15 | 18 | 12 | 13 | 34 | 37 | 63 | 41 | 33 | 38 | 0.62 | 0.62 | 0.76 | 0.56 | 0.64 | 0.66 |
| EDD | Low | 14 | 15 | 16 | 18 | 14 | 21 | 38 | 17 | 32 | 39 | 37 | 29 | 0.63 | 0.12 | 0.50 | 0.54 | 0.62 | 0.28 |
| SPT | Low | 9 | 16 | 9 | 12 | 18 | 15 | 29 | 31 | 31 | 26 | 24 | 16 | 0.69 | 0.48 | 0.71 | 0.54 | 0.25 | 0.06 |
| SPT | Low | 8 | 8 | 12 | 10 | 12 | 11 | 36 | 45 | 33 | 27 | 22 | 19 | 0.78 | 0.82 | 0.64 | 0.63 | 0.45 | 0.42 |
| SPT | Low | 9 | 10 | 9 | 13 | 11 | 10 | 13 | 65 | 20 | 61 | 28 | 11 | 0.31 | 0.85 | 0.55 | 0.79 | 0.61 | 0.09 |
| FIFO | Medium | 23 | 28 | 27 | 29 | 26 | 17 | 58 | 38 | 29 | 91 | 39 | 25 | 0.60 | 0.26 | 0.07 | 0.68 | 0.33 | 0.32 |
| FIFO | Medium | 22 | 25 | 28 | 23 | 33 | 24 | 26 | 34 | 45 | 65 | 46 | 34 | 0.15 | 0.26 | 0.38 | 0.65 | 0.28 | 0.29 |
| FIFO | Medium | 22 | 24 | 28 | 23 | 27 | 23 | 56 | 41 | 50 | 79 | 73 | 29 | 0.61 | 0.41 | 0.44 | 0.71 | 0.63 | 0.21 |
| EDD | Medium | 21 | 27 | 35 | 23 | 31 | 23 | 37 | 75 | 42 | 60 | 47 | 42 | 0.43 | 0.64 | 0.17 | 0.62 | 0.34 | 0.45 |
| EDD | Medium | 22 | 30 | 25 | 28 | 19 | 28 | 32 | 92 | 39 | 39 | 35 | 41 | 0.31 | 0.67 | 0.36 | 0.28 | 0.46 | 0.32 |
| EDD | Medium | 22 | 24 | 31 | 24 | 29 | 24 | 28 | 42 | 45 | 72 | 45 | 50 | 0.21 | 0.43 | 0.31 | 0.67 | 0.36 | 0.52 |
| SPT | Medium | 23 | 26 | 14 | 26 | 27 | 20 | 41 | 40 | 88 | 74 | 95 | 59 | 0.44 | 0.35 | 0.84 | 0.65 | 0.72 | 0.66 |
| SPT | Medium | 24 | 22 | 21 | 29 | 25 | 23 | 64 | 24 | 59 | 36 | 26 | 36 | 0.63 | 0.08 | 0.64 | 0.19 | 0.04 | 0.36 |
| SPT | Medium | 23 | 22 | 16 | 33 | 33 | 26 | 34 | 42 | 23 | 87 | 38 | 49 | 0.32 | 0.48 | 0.30 | 0.62 | 0.13 | 0.47 |
| FIFO | High | 40 | 36 | 20 | 36 | 35 | 34 | 48 | 64 | 56 | 43 | 64 | 47 | 0.17 | 0.44 | 0.64 | 0.16 | 0.45 | 0.28 |
| FIFO | High | 42 | 36 | 23 | 37 | 36 | 34 | 116 | 74 | 62 | 42 | 49 | 51 | 0.64 | 0.51 | 0.63 | 0.12 | 0.27 | 0.33 |
| FIFO | High | 40 | 44 | 33 | 48 | 34 | 30 | 78 | 62 | 81 | 87 | 81 | 64 | 0.49 | 0.29 | 0.59 | 0.45 | 0.58 | 0.53 |
| EDD | High | 41 | 42 | 33 | 44 | 35 | 30 | 97 | 69 | 50 | 70 | 49 | 52 | 0.58 | 0.39 | 0.34 | 0.37 | 0.29 | 0.42 |
| EDD | High | 44 | 40 | 35 | 44 | 35 | 31 | 51 | 65 | 74 | 67 | 55 | 87 | 0.14 | 0.38 | 0.53 | 0.34 | 0.36 | 0.64 |
| EDD | High | 43 | 37 | 25 | 39 | 39 | 37 | 56 | 55 | 30 | 53 | 49 | 50 | 0.23 | 0.33 | 0.17 | 0.26 | 0.20 | 0.26 |
| SPT | High | 40 | 36 | 20 | 36 | 35 | 34 | 69 | 43 | 31 | 63 | 69 | 53 | 0.42 | 0.16 | 0.35 | 0.43 | 0.49 | 0.36 |
| SPT | High | 41 | 36 | 19 | 37 | 34 | 34 | 54 | 55 | 32 | 82 | 48 | 57 | 0.24 | 0.35 | 0.41 | 0.55 | 0.29 | 0.40 |
| SPT | High | 41 | 39 | 33 | 44 | 35 | 30 | 42 | 65 | 38 | 84 | 56 | 44 | 0.02 | 0.40 | 0.13 | 0.48 | 0.38 | 0.32 |

Table 5.12 Comparison of Maximum Flowtime Job.

| Sched. Rule | Job <br> Arrival | SIMULATION RESULTS |  |  |  |  |  | ANN MODEL |  |  |  |  |  | DIFFERENCE (\%) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 | J1 | J2 | J3 | J4 | J5 | J6 |
| FIFO | Low | 60.3 | 77.5 | 75.9 | 87.2 | 80.3 | 66.0 | 72.1 | 286.7 | 126.5 | 305.1 | 171.4 | 77.6 | 0.16 | 0.73 | 0.40 | 0.71 | 0.53 | 0.15 |
| FIFO | Low | 62.2 | 67.5 | 71.5 | 61.0 | 90.0 | 84.4 | 113.7 | 178.5 | 300.4 | 138.9 | 247.4 | 246.7 | 0.45 | 0.62 | 0.76 | 0.56 | 0.64 | 0.66 |
| FIFO | Low | 62.5 | 73.5 | 70.9 | 67.3 | 76.1 | 69.3 | 86.4 | 83.3 | 141.8 | 145.7 | 201.2 | 95.7 | 0.28 | 0.12 | 0.50 | 0.54 | 0.62 | 0.28 |
| EDD | Low | 63.3 | 80.5 | 77.9 | 89.2 | 81.3 | 67.0 | 159.7 | 109.2 | 83.7 | 279.8 | 121.9 | 98.5 | 0.60 | 0.26 | 0.07 | 0.68 | 0.33 | 0.32 |
| EDD | Low | 61.0 | 71.5 | 64.0 | 72.0 | 62.0 | 63.6 | 72.1 | 97.2 | 102.9 | 203.4 | 86.4 | 90.1 | 0.15 | 0.26 | 0.38 | 0.65 | 0.28 | 0.29 |
| EDD | Low | 73.0 | 76.7 | 75.0 | 74.0 | 82.4 | 63.0 | 185.9 | 131.0 | 133.9 | 254.3 | 222.8 | 79.4 | 0.61 | 0.41 | 0.44 | 0.71 | 0.63 | 0.21 |
| SPT | Low | 57.8 | 67.0 | 76.7 | 64.3 | 89.6 | 58.2 | 90.9 | 188.0 | 218.3 | 79.8 | 107.0 | 66.1 | 0.36 | 0.64 | 0.65 | 0.19 | 0.16 | 0.12 |
| SPT | Low | 60.2 | 67.5 | 68.5 | 60.0 | 90.0 | 83.4 | 75.6 | 91.3 | 241.1 | 62.4 | 164.5 | 113.5 | 0.20 | 0.26 | 0.72 | 0.04 | 0.45 | 0.27 |
| SPT | Low | 59.5 | 70.5 | 68.9 | 65.3 | 74.1 | 66.3 | 117.3 | 109.9 | 203.2 | 102.2 | 102.5 | 99.4 | 0.49 | 0.36 | 0.66 | 0.36 | 0.28 | 0.33 |
| FIFO | Medium | 83.0 | 71.9 | 77.0 | 78.0 | 97.5 | 92.4 | 221.3 | 78.4 | 216.4 | 96.9 | 101.4 | 144.6 | 0.63 | 0.08 | 0.64 | 0.19 | 0.04 | 0.36 |
| FIFO | Medium | 69.0 | 73.7 | 80.7 | 65.4 | 84.2 | 82.7 | 101.9 | 140.8 | 116.0 | 172.4 | 96.9 | 155.9 | 0.32 | 0.48 | 0.30 | 0.62 | 0.13 | 0.47 |
| FIFO | Medium | 90.9 | 81.7 | 88.4 | 65.9 | 88.7 | 97.4 | 109.1 | 145.3 | 247.6 | 78.7 | 162.2 | 134.6 | 0.17 | 0.44 | 0.64 | 0.16 | 0.45 | 0.28 |
| EDD | Medium | 84.0 | 73.9 | 80.0 | 78.0 | 98.5 | 92.4 | 97.4 | 120.1 | 169.2 | 118.8 | 118.2 | 358.6 | 0.14 | 0.38 | 0.53 | 0.34 | 0.17 | 0.74 |
| EDD | Medium | 77.6 | 75.2 | 76.5 | 75.1 | 78.9 | 90.2 | 101.0 | 111.7 | 91.8 | 102.1 | 140.2 | 473.7 | 0.23 | 0.33 | 0.17 | 0.26 | 0.44 | 0.81 |
| EDD | Medium | 80.3 | 98.1 | 82.1 | 70.4 | 99.4 | 92.4 | 138.5 | 117.2 | 127.3 | 123.2 | 278.2 | 377.8 | 0.42 | 0.16 | 0.35 | 0.43 | 0.64 | 0.76 |
| SPT | Medium | 72.2 | 75.1 | 74.3 | 66.0 | 121.2 | 86.2 | 159.8 | 240.4 | 285.0 | 186.0 | 390.5 | 167.1 | 0.55 | 0.69 | 0.74 | 0.65 | 0.69 | 0.48 |
| SPT | Medium | 82.0 | 69.9 | 74.0 | 78.0 | 96.5 | 92.4 | 164.0 | 374.8 | 141.9 | 86.2 | 434.1 | 519.5 | 0.50 | 0.81 | 0.48 | 0.10 | 0.78 | 0.82 |
| SPT | Medium | 74.3 | 92.1 | 78.1 | 66.4 | 96.4 | 96.4 | 191.0 | 347.2 | 195.3 | 204.7 | 139.2 | 626.3 | 0.61 | 0.73 | 0.60 | 0.68 | 0.31 | 0.85 |
| FIFO | High | 617.5 | 707.9 | 639.7 | 690.6 | 718.3 | 627.1 | 2127.0 | 1533.8 | 852.9 | 736.6 | 1044.8 | 1923.2 | 0.71 | 0.54 | 0.25 | 0.06 | 0.31 | 0.67 |
| FIFO | High | 631.8 | 740.8 | 648.7 | 751.5 | 736.9 | 648.5 | 1737.5 | 2000.0 | 1189.2 | 1298.1 | 937.8 | 1134.8 | 0.64 | 0.63 | 0.45 | 0.42 | 0.21 | 0.43 |
| FIFO | High | 621.5 | 711.9 | 641.7 | 692.6 | 724.3 | 633.1 | 1381.2 | 3340.5 | 1633.3 | 761.8 | 1291.2 | 974.0 | 0.55 | 0.79 | 0.61 | 0.09 | 0.44 | 0.35 |
| EDD | High | 632.8 | 742.8 | 651.7 | 748.5 | 737.9 | 648.5 | 861.4 | 1114.1 | 1161.6 | 1996.1 | 885.5 | 1791.0 | 0.27 | 0.33 | 0.44 | 0.63 | 0.17 | 0.64 |
| EDD | High | 631.8 | 740.8 | 648.7 | 754.5 | 736.9 | 648.5 | 1505.2 | 1580.3 | 997.9 | 823.1 | 1310.0 | 1333.0 | 0.58 | 0.53 | 0.35 | 0.08 | 0.44 | 0.51 |
| EDD | High | 634.8 | 742.8 | 654.7 | 749.5 | 737.9 | 649.5 | 888.8 | 1287.4 | 4114.9 | 2105.8 | 2066.1 | 1750.8 | 0.29 | 0.42 | 0.84 | 0.64 | 0.64 | 0.63 |
| SPT | High | 630.8 | 738.8 | 645.7 | 748.5 | 735.9 | 648.5 | 984.1 | 1029.0 | 1189.4 | 1096.1 | 2032.4 | 1333.0 | 0.36 | 0.28 | 0.46 | 0.32 | 0.64 | 0.51 |
| SPT | High | 618.5 | 707.9 | 637.7 | 691.6 | 720.3 | 630.1 | 897.9 | 2123.8 | 989.5 | 1440.8 | 1404.6 | 887.9 | 0.31 | 0.67 | 0.36 | 0.52 | 0.49 | 0.29 |
| SPT | High | 620.5 | 708.9 | 640.7 | 690.6 | 724.3 | 633.1 | 3900.4 | 2017.7 | 2254.1 | 2037.2 | 1713.7 | 1040.142 | 0.84 | 0.65 | 0.72 | 0.66 | 0.58 | 0.39 |
| Jn = Job \#1 |  | b \#2 |  | Job \#3 |  | Jn = Job \# |  | Jn = Job \#5 |  | n = Job \#6 |  |  |  |  |  |  |  |  |  |

Table 5.13 Comparison of Average Machine Utilization.

| Sched. Rule | JobArrival | SIMULATION RESULTS |  |  |  |  |  | ANN MODEL |  |  |  |  |  | DIFFERENCE (\%) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| FIFO | Low | 0.336 | 0.259 | 0.270 | 0.210 | 0.341 | 0.371 | 0.358 | 0.447 | 0.297 | 0.309 | 0.483 | 0.468 | 0.06 | 0.42 | 0.09 | 0.32 | 0.29 | 0.21 |
| FIFO | Low | 0.350 | 0.260 | 0.256 | 0.206 | 0.367 | 0.410 | 1.254 | 1.365 | 0.512 | 1.105 | 0.703 | 0.453 | 0.72 | 0.81 | 0.50 | 0.81 | 0.48 | 0.10 |
| FIFO | Low | 0.318 | 0.221 | 0.224 | 0.178 | 0.321 | 0.355 | 1.185 | 0.904 | 0.576 | 0.671 | 0.803 | 1.095 | 0.73 | 0.76 | 0.61 | 0.73 | 0.60 | 0.68 |
| EDD | Low | 0.344 | 0.258 | 0.229 | 0.257 | 0.376 | 0.407 | 0.918 | 0.953 | 0.382 | 0.898 | 0.803 | 0.478 | 0.63 | 0.73 | 0.40 | 0.71 | 0.53 | 0.15 |
| EDD | Low | 0.329 | 0.309 | 0.263 | 0.255 | 0.310 | 0.335 | 0.861 | 0.817 | 1.106 | 0.580 | 0.853 | 0.979 | 0.62 | 0.62 | 0.76 | 0.56 | 0.64 | 0.66 |
| EDD | Low | 0.318 | 0.288 | 0.224 | 0.278 | 0.388 | 0.455 | 0.863 | 0.326 | 0.448 | 0.602 | 1.025 | 0.628 | 0.63 | 0.12 | 0.50 | 0.54 | 0.62 | 0.28 |
| SPT | Low | 0.299 | 0.258 | 0.197 | 0.117 | 0.330 | 0.404 | 0.965 | 0.499 | 0.680 | 0.254 | 0.440 | 0.431 | 0.69 | 0.48 | 0.71 | 0.54 | 0.25 | 0.06 |
| SPT | Low | 0.308 | 0.242 | 0.230 | 0.104 | 0.339 | 0.356 | 1.386 | 1.361 | 0.633 | 0.281 | 0.622 | 0.615 | 0.78 | 0.82 | 0.64 | 0.63 | 0.45 | 0.42 |
| SPT | Low | 0.318 | 0.154 | 0.224 | 0.078 | 0.254 | 0.255 | 0.459 | 1.003 | 0.498 | 0.366 | 0.647 | 0.281 | 0.31 | 0.85 | 0.55 | 0.79 | 0.61 | 0.09 |
| FIFO | Medium | 0.563 | 0.458 | 0.476 | 0.346 | 0.652 | 0.676 | 1.420 | 0.622 | 0.511 | 1.086 | 0.978 | 0.994 | 0.60 | 0.26 | 0.07 | 0.68 | 0.33 | 0.32 |
| FIFO | Medium | 0.552 | 0.486 | 0.480 | 0.334 | 0.664 | 0.692 | 0.652 | 0.661 | 0.771 | 0.944 | 0.926 | 0.980 | 0.15 | 0.26 | 0.38 | 0.65 | 0.28 | 0.29 |
| FIFO | Medium | 0.579 | 0.463 | 0.501 | 0.338 | 0.654 | 0.705 | 1.474 | 0.791 | 0.895 | 1.161 | 1.768 | 0.889 | 0.61 | 0.41 | 0.44 | 0.71 | 0.63 | 0.21 |
| EDD | Medium | 0.648 | 0.671 | 0.534 | 0.570 | 0.833 | 0.896 | 1.142 | 1.863 | 0.641 | 1.487 | 1.263 | 1.636 | 0.43 | 0.64 | 0.17 | 0.62 | 0.34 | 0.45 |
| EDD | Medium | 0.582 | 0.466 | 0.394 | 0.684 | 0.652 | 0.727 | 0.847 | 1.429 | 0.615 | 0.953 | 1.201 | 1.065 | 0.31 | 0.67 | 0.36 | 0.28 | 0.46 | 0.32 |
| EDD | Medium | 0.679 | 0.463 | 0.601 | 0.538 | 0.654 | 0.705 | 0.864 | 0.810 | 0.872 | 1.614 | 1.015 | 1.469 | 0.21 | 0.43 | 0.31 | 0.67 | 0.36 | 0.52 |
| SPT | Medium | 0.510 | 0.229 | 0.414 | 0.039 | 0.716 | 0.660 | 0.909 | 0.352 | 2.602 | 0.111 | 2.519 | 1.947 | 0.44 | 0.35 | 0.84 | 0.65 | 0.72 | 0.66 |
| SPT | Medium | 0.582 | 0.466 | 0.394 | 0.084 | 0.652 | 0.727 | 1.552 | 0.508 | 1.107 | 0.104 | 0.678 | 1.138 | 0.63 | 0.08 | 0.64 | 0.19 | 0.04 | 0.36 |
| SPT | Medium | 0.554 | 0.485 | 0.482 | 0.328 | 0.677 | 0.637 | 0.819 | 0.926 | 0.693 | 0.865 | 0.780 | 1.201 | 0.32 | 0.48 | 0.30 | 0.62 | 0.13 | 0.47 |
| FIFO | High | 0.999 | 0.791 | 0.704 | 0.639 | 1.000 | 1.000 | 1.199 | 1.406 | 1.971 | 0.763 | 1.829 | 1.382 | 0.17 | 0.44 | 0.64 | 0.16 | 0.45 | 0.28 |
| FIFO | High | 0.998 | 0.823 | 0.786 | 0.892 | 1.000 | 1.000 | 2.756 | 1.692 | 2.119 | 1.013 | 1.361 | 1.500 | 0.64 | 0.51 | 0.63 | 0.12 | 0.27 | 0.33 |
| FIFO | High | 0.998 | 0.823 | 0.786 | 1.000 | 1.000 | 1.000 | 1.946 | 1.160 | 1.929 | 1.813 | 2.382 | 2.133 | 0.49 | 0.29 | 0.59 | 0.45 | 0.58 | 0.53 |
| EDD | High | 0.999 | 1.000 | 0.804 | 0.939 | 1.000 | 1.000 | 2.363 | 1.643 | 1.218 | 1.494 | 1.400 | 1.733 | 0.58 | 0.39 | 0.34 | 0.37 | 0.29 | 0.42 |
| EDD | High | 0.998 | 0.823 | 0.786 | 1.000 | 1.000 | 1.000 | 1.157 | 1.337 | 1.662 | 1.523 | 1.571 | 2.806 | 0.14 | 0.38 | 0.53 | 0.34 | 0.36 | 0.64 |
| EDD | High | 1.000 | 1.000 | 0.997 | 0.767 | 1.000 | 1.000 | 1.302 | 1.486 | 1.196 | 1.042 | 1.256 | 1.351 | 0.23 | 0.33 | 0.17 | 0.26 | 0.20 | 0.26 |
| SPT | High | 0.792 | 0.668 | 0.514 | 0.299 | 0.800 | 1.000 | 1.366 | 0.798 | 0.797 | 0.523 | 1.577 | 1.559 | 0.42 | 0.16 | 0.35 | 0.43 | 0.49 | 0.36 |
| SPT | High | 0.800 | 0.871 | 0.797 | 0.667 | 0.800 | 1.000 | 1.054 | 1.331 | 1.342 | 1.478 | 1.129 | 1.676 | 0.24 | 0.35 | 0.41 | 0.55 | 0.29 | 0.40 |
| SPT | High | 0.898 | 0.523 | 0.686 | 0.800 | 1.000 | 1.000 | 0.920 | 0.872 | 0.790 | 1.527 | 1.600 | 1.467 | 0.02 | 0.40 | 0.13 | 0.48 | 0.38 | 0.32 |

Table 5.14 Comparison of Average Job Q Length for the Machine.

| Sched. Rule | Job <br> Arrival | SIMULATION RESULTS |  |  |  |  |  | ANN MODEL |  |  |  |  |  | DIFFERENCE (\%) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF | MA | MB | MC | MD | ME | MF |
| FIFO | Low | 0.033 | 0.046 | 0.027 | 0.010 | 0.083 | 0.146 | 0.040 | 0.081 | 0.076 | 0.012 | 0.152 | 0.202 | 0.17 | 0.44 | 0.64 | 0.16 | 0.45 | 0.28 |
| FIFO | Low | 0.029 | 0.062 | 0.029 | 0.042 | 0.037 | 0.051 | 0.113 | 0.326 | 0.119 | 0.155 | 0.098 | 0.058 | 0.74 | 0.81 | 0.76 | 0.73 | 0.62 | 0.12 |
| FIFO | Low | 0.029 | 0.035 | 0.063 | 0.021 | 0.057 | 0.079 | 0.064 | 0.070 | 0.162 | 0.035 | 0.239 | 0.158 | 0.55 | 0.50 | 0.61 | 0.40 | 0.76 | 0.50 |
| EDD | Low | 0.027 | 0.815 | 0.095 | 0.022 | 0.121 | 0.091 | 0.087 | 4.373 | 0.359 | 0.078 | 0.276 | 0.197 | 0.69 | 0.81 | 0.73 | 0.71 | 0.56 | 0.54 |
| EDD | Low | 0.027 | 0.038 | 0.047 | 0.027 | 0.094 | 0.178 | 0.104 | 0.073 | 0.118 | 0.058 | 0.260 | 0.471 | 0.74 | 0.48 | 0.60 | 0.53 | 0.64 | 0.62 |
| EDD | Low | 0.030 | 0.042 | 0.038 | 0.021 | 0.087 | 0.165 | 0.085 | 0.047 | 0.118 | 0.025 | 0.255 | 0.228 | 0.65 | 0.10 | 0.68 | 0.15 | 0.66 | 0.28 |
| SPT | Low | 0.028 | 0.085 | 0.090 | 0.011 | 0.165 | 0.260 | 0.089 | 0.382 | 0.130 | 0.027 | 0.195 | 0.662 | 0.69 | 0.78 | 0.31 | 0.60 | 0.15 | 0.61 |
| SPT | Low | 0.049 | 0.026 | 0.089 | 0.012 | 0.068 | 0.068 | 0.095 | 0.144 | 0.578 | 0.016 | 0.092 | 0.116 | 0.48 | 0.82 | 0.85 | 0.26 | 0.26 | 0.41 |
| SPT | Low | 0.024 | 0.036 | 0.034 | 0.017 | 0.083 | 0.159 | 0.082 | 0.098 | 0.075 | 0.018 | 0.133 | 0.283 | 0.71 | 0.64 | 0.55 | 0.07 | 0.38 | 0.44 |
| FIFO | Medium | 0.129 | 0.137 | 0.182 | 0.050 | 0.334 | 0.382 | 0.280 | 0.370 | 0.854 | 0.156 | 0.945 | 1.312 | 0.54 | 0.63 | 0.79 | 0.68 | 0.65 | 0.71 |
| FIFO | Medium | 0.191 | 0.151 | 0.243 | 0.063 | 0.447 | 0.503 | 0.255 | 0.277 | 0.619 | 0.095 | 0.623 | 1.360 | 0.25 | 0.45 | 0.61 | 0.33 | 0.28 | 0.63 |
| FIFO | Medium | 0.162 | 0.208 | 0.197 | 0.038 | 0.299 | 0.529 | 0.172 | 0.359 | 0.217 | 0.056 | 0.424 | 0.667 | 0.06 | 0.42 | 0.09 | 0.32 | 0.29 | 0.21 |
| EDD | Medium | 0.159 | 0.167 | 0.202 | 0.070 | 0.344 | 0.392 | 0.231 | 0.212 | 0.360 | 0.186 | 0.509 | 0.470 | 0.31 | 0.21 | 0.44 | 0.63 | 0.32 | 0.17 |
| EDD | Medium | 0.159 | 0.167 | 0.202 | 0.070 | 0.344 | 0.392 | 0.488 | 0.292 | 0.311 | 0.076 | 0.657 | 0.697 | 0.67 | 0.43 | 0.35 | 0.08 | 0.48 | 0.44 |
| EDD | Medium | 0.167 | 0.135 | 0.168 | 0.140 | 0.322 | 0.505 | 0.261 | 0.196 | 1.056 | 0.393 | 0.463 | 1.414 | 0.36 | 0.31 | 0.84 | 0.64 | 0.30 | 0.64 |
| SPT | Medium | 0.196 | 0.183 | 0.171 | 0.046 | 0.396 | 0.423 | 0.273 | 0.549 | 0.487 | 0.057 | 1.044 | 0.505 | 0.28 | 0.67 | 0.65 | 0.19 | 0.62 | 0.16 |
| SPT | Medium | 0.181 | 0.121 | 0.233 | 0.043 | 0.447 | 0.503 | 0.333 | 0.188 | 0.820 | 0.045 | 0.515 | 0.920 | 0.46 | 0.36 | 0.72 | 0.04 | 0.13 | 0.45 |
| SPT | Medium | 0.107 | 0.075 | 0.128 | 0.100 | 0.282 | 0.445 | 0.157 | 0.156 | 0.378 | 0.157 | 0.531 | 0.615 | 0.32 | 0.52 | 0.66 | 0.36 | 0.47 | 0.28 |
| FIFO | High | 0.590 | 35.663 | 7.995 | 37.049 | 0.883 | 1.083 | 1.630 | 69.543 | 18.916 | 42.943 | 1.150 | 1.867 | 0.64 | 0.49 | 0.58 | 0.14 | 0.23 | 0.42 |
| FIFO | High | 0.536 | 48.730 | 3.926 | 28.073 | 2.083 | 1.511 | 1.102 | 68.665 | 6.450 | 45.619 | 3.096 | 1.805 | 0.51 | 0.29 | 0.39 | 0.38 | 0.33 | 0.16 |
| FIFO | High | 0.516 | 48.710 | 3.916 | 28.123 | 2.053 | 1.481 | 1.391 | 119.561 | 5.933 | 59.460 | 2.464 | 2.296 | 0.63 | 0.59 | 0.34 | 0.53 | 0.17 | 0.35 |
| EDD | High | 0.590 | 35.663 | 7.995 | 37.049 | 0.883 | 1.083 | 0.670 | 64.639 | 12.720 | 56.416 | 1.200 | 1.894 | 0.12 | 0.45 | 0.37 | 0.34 | 0.26 | 0.43 |
| EDD | High | 0.600 | 35.683 | 8.025 | 37.079 | 0.893 | 1.083 | 0.817 | 85.010 | 11.236 | 58.267 | 1.122 | 2.134 | 0.27 | 0.58 | 0.29 | 0.36 | 0.20 | 0.49 |
| EDD | High | 0.630 | 35.663 | 8.055 | 37.069 | 0.883 | 1.103 | 0.945 | 76.081 | 13.963 | 104.032 | 1.193 | 1.719 | 0.33 | 0.53 | 0.42 | 0.64 | 0.26 | 0.36 |
| SPT | High | 0.620 | 35.673 | 8.015 | 37.049 | 0.893 | 1.083 | 1.105 | 54.882 | 50.383 | 105.447 | 3.142 | 3.193 | 0.44 | 0.35 | 0.84 | 0.65 | 0.72 | 0.66 |
| SPT | High | 0.620 | 35.693 | 8.045 | 37.109 | 0.913 | 1.083 | 1.653 | 38.938 | 22.604 | 46.066 | 0.950 | 1.694 | 0.63 | 0.08 | 0.64 | 0.19 | 0.04 | 0.36 |
| SPT | High | 0.526 | 48.740 | 3.926 | 28.143 | 2.053 | 1.481 | 0.631 | 86.649 | 10.993 | 33.615 | 3.754 | 2.047 | 0.17 | 0.44 | 0.64 | 0.16 | 0.45 | 0.28 |

### 5.4 Discussion

Samples of the results are compared graphically between the results from ARENA simulation and the ANN scheduling model as shown in Figures 5.2 to 5.5. Overall, ANN model resulted in moderately reliable prediction for the following:
(i) Prediction for the number completed jobs for EDD with high job arrival (Figure 5.2 (h), SPT with medium and high job arrival (Fig. 5.2(f and i)
(ii) Prediction for maximum flowtime for SPT with low, and SPT with medium job arrival (Fig. 5.3 (c) and (f))
(iii) Prediction for average machine utilization for SPT with medium job arrival (Figure 5.4 f )
(iv) Prediction on average length of queue. The graphs in Figure 5.5 suggest that both techniques gave almost similar patterns.

In general, the above results suggest that the ANN schedule model needs further improvement to provide more consistent results for other scheduling scenarios. High variability in the dynamic job shop environment may have contributed to the difficulty in getting better results. The proposed theoretical framework as shown in Figure 3-2 can be used as a basis for further investigation.


Figure 5.2 Comparison of Number Completed Jobs.


Figure 5.3 Comparison of Maximum Flowtime Job.


Figure 5.4 Comparison of Average Machine Utilization.


Figure 5.5 Comparison of Average Job Q Length for the Machine.

## CHAPTER 6

## CONCLUSSIONS

In the first phase of this research, a simulation study for various job shop scheduling scenarios were evaluated using ARENA simulation software package. In the second phase, an ANN scheduling model was developed using Multilayer Perceptron model. The ANN model was trained and tested using various scheduling scenarios generated from Arena simulation.

This study has provided better understanding on the complexity of dynamic scheduling. An ANN model to predict various scheduling scenario has been developed. The experimental results suggest that the model can provided moderately reliable prediction results for selected job shop scenario when predicting the number completed jobs, maximum flowtime, average machine utilization, and average length of queue. There were also some scheduling scenarios where the model did not provide good prediction results. The finding suggests that high variability in the dynamic job shop environment and insufficient representative scenarios may have contributed to the difficulty in getting better results. Thus, the present ANN scheduling model needs further improvement to provide more consistent results.

The following are suggestions for further investigation:
(i) Fine tune the ANN scheduling model to give more consistent results (ii) Consider more variety of job shop sizes (iii) Incorporate an expert system in realizing an intelligent dynamic scheduling system.

The theoretical framework as proposed in Figure 3-2 can be used as a basis for further investigation.

## LIST OF REFERENCES

Abumaizar, R. J., and Svestka, J. A., 1997. Rescheduling job shops under disruptions. International Journal of Production Research, 35, 2065-2082.

Azizoğlu M. and Alagoz, O, (2003), Rescheduling of identical parallel machines under machine eligibility constraints, European Journal of Operational Research, Vol. 149, pp. 523-532

Azizoğlu M. and Alagoz, O, (2002), Parallel machine rescheduling with machine disruptions, Middle East Technical University, Department of Industrial Engineering, Turkey, pp. 1-20

Baker, K. R. (1984), Sequencing rules and due-dates assignment in a job-shop, Management Science, Vol. 30: pp. 1093-1104.

Baker K. R. (1974), Introduction to Sequencing and Scheduling. New York: John Willey \& Sons.

Balasubramanian, J., and Grossmann, I. E. (2002), A novel branch and bound algorithm for scheduling flowshop plants with uncertain processing times, Computers and Chemical Engineering. Vol. 26: pp. 41-57.

Banks, J. (1998), Handbook of Simulation, New York: John Willey and Sons, Inc..

Bean, James C., John R. Birge, John Mittenthal, and Charles E. Noon, "Matchup scheduling with multiple resources, release dates, and disruptions," Operations Research, Volume 39, Number 3, pages 470-483, 1991.

Belz, R., and Martens, P., (1996), Combining knowledge-based system and simulation to solve resceduling problems, Decision Support Systems, Vol. 17: pp. 141-157

Benjaafar, S. and Sheikhzadeh, M. (1997), Scheduling policies, batch sizes, and manufacturing lead times. IEE Transaction, Vol. 29: pp. 159-166

Bilkay O. Anlagan, O., and Kilic, S. E., (2004), Job shop scheduling using fuzzy logic, Int J Adv Manuf Technol. Vol. 23, pp. 606-619

Black, J.T., (1983), Manufacturing systems, Kluwer, Norwell, Massachusetts.

Blazewicz, J., Domschke, W., and Pesch, E. (1996), The Job Shop Scheduling Problem: Conventional and New Techniques, European Journal of Operation Research. Vol. 93: pp. 1-33.

Blazewicz, J. et al. (1993), Scheduling in Computer and Manufacturing Systems, Springer-Verlag,

Brizuela, C.A., and Sannomiya, N., (1999), From the classical Job Shop to a real Problem: A Genetic Algorithm Approach. Kyoto Institute of technology, Japan.

Brucker, P. (1995), Scheduling Algorithm, New York: Springer Verlag.

Buxey, G. (1989), Production Scheduling: Practice and theory, European Journal of Operation Research, Vol. 39: pp. 17-31.

Cave, A., Nahavandi, S., and Kouzani, A., (2002), Simulation Optimization for Process Scheduling Trough Simulated Annealing, Proceedings of the 2002 Winter Simulation Conference

Chang, F. C. R. (1996), A study of due-date assignment rules with constrained tightness in a dynamic job shop, Discrete Applied Mathematics, Vol. 77: pp. 185-200.

Cheng, R., et al. (1996), A bi-criteria optimization - minimizing the integral value and spread of the fuzzy makespan of job shop scheduling problems, Computers ind. Engng, Vol. 30(4): pp. 983-997.

Cheng, T. C. E. and Kovalov, M. Y. (2001), Single Machine batch Scheduling with Sequential Job Processing. IEE Transaction, Vol. 33: pp. 413-420.

Cheng, T. C. E., Liu Z., and Wenci, (2001), Scheduling jobs with release dates and deadlines on batch processing machine, IEE Transaction. Vol. 33: pp. 685690.

Chong, C. S., Sivakumar, A. I. and Gay, R. (2003) Simulation Based Scheduling for Dynamic Discrete Manufacturing, Proceeding of the 2003 Winter Simulation Conference, pp. 1465-1473

Church, L.K., Uzsoy, R., (1992). Analysis of periodic and event driven rescheduling policies in dynamic shops. International Journal of Computer Integrated Manufacturing Vol. 5 (3), pp. 153-163.

Chryssolouris G. (1992), Manufacturing Systems. Theory and Practice, New York: Springer-Verlag.

Conway, R., Maxwell, W., and Miller, L. (1967), Theory of Scheduling, AddisonWesley, Publishing Company.

Cottet, F., Kaiser, J. D. C., and Mammeri, Z., (2002), Scheduling in Real-Time System, Chichester, England: John Wiley \& Son, Ltd.

Chun, H. W. and Wong, R. Y. M., 2003, an agent-based negotiation algorithm for dynamic scheduling and rescheduling, Advanced Engineering Informatics, Vol. 17, pp. 1-22

Dhingra, J. S., Musser, K. L., and Blankenship, G. L., 1992. Real-time operations scheduling for flexible manufacturing systems. Proceeding of the 1992 Winter Simulation Conference, 849-855.

Diaz, A. R., Tchernykh,A., and Ecker,K. H., 2003, Algorithms for dynamic scheduling of unit execution time tasks, European Journal of Operational Research 146, pp. 403-416

Dominic, P. D. D., and Kaliyamoorty, S. (2004), Efficient Dispatching Rules for Dynamic Job Shop Scheduling, Journal of Manufacturing Technology. Vol. 24: pp. 70-75.

Drexl, A. (1997), Lot Sizing and Scheduling, - Survey and Extension, European Journal of Operation Research, Vol. 99, 1997, pp. 271-235.

Dunstall, S. and Wirth, A. (2001), Models and Algorithms for Machine Scheduling with setup Times. Elvers, D. A., and Taube (1988), L. R., Time completion of various dispatching rules in job shop, OMEGA. Vol. 11: pp. 81-89.

Elvers, D.A. and Taube, L.R., (1983), Time completion for various dispatching rules in job shops, Omega, Vol. II (1), pp. 81-9.

El-Bouri, A., Balakrishnan, S., , and Popplewell, N., (2000), Sequencing jobs on a single machine: A neural network approach, European Journal of Operational Research, Vol. 126, pp. 474-490.

Emery, J. C. (1969), Job Shop Scheduling by Mean Simulation and an OptimumSeeking Search, University of Pennsylvania, Philadelphia, Pennsylvania: pp. 363-372.

Fang, J., and Xi, Y., 1997. A rolling horizon job shop rescheduling strategy in the dynamic environment. The International Journal of Advanced Manufacturing Technology, 13, 227-232

Fonseca, D. J., and Navaresse, D. (2002), Artificial neural networks for job shop simulation, Engineering Informatics, Vol. 16: pp. 241-246.

French, S., (1982), Scheduling and Sequencing, Chicherster, London: John Willey \& Sons (Ellis Horwood Ltd),

Fry, D., Phillipoom, P.R., and Blackstone, J. H. (1988), A simulation study of processing time dispatching rules, Journal of Operation Management. Vol. 7: pp. 77-92.

Graves S. C. (1981), A Review of Production Scheduling, Operation Research, Vol. 29: pp. 647-675.

Guh, R-S., 2004, Optimizing Feed forward Neural Network for Control Chart Pattern Recognition Through Genetic Algorithms, International Journal of Pattern Recognition and Artificial Intelligent. Vol. 18(2), pp. 75-99.

Gupta, S. K. (1981), Production Scheduling Techniques. K. P. Bagchi \& Company

Hassan, A, (2002), On-line recognition of developing control chart pattern, PhD dissertation, University Teknologi Malaysia.

Hall, N. G. (1996), A Survey of Machine Scheduling Problems with Blocking and No-wait in Process. Operation Research, Vol. 44: pp. 510-525.

Heywood, M. I., Chan, M.C., and Chatwin C. R., (1997), Aplication of stochastic real valued reinforcement neural network to batch production rescheduling, Proceedings of the Institution of Mechanical Engineers, , 211, , 591-603

Hoitomt, D. J., and Luh, P. B. (1993), Scheduling the Dynamic Job Shop. IEEE. pp. 71-76.

Holloway, C.A., and Nelson, R.T., (1974). Job shop scheduling with due dates and variable processing times. Management Science, Vol. 20 (9), pp. 65-75.

Holthaus, O. (1999), Scheduling in job shops with machine breakdowns - an experimental study, Computers \& Industrial Engineering. Vol. 36: pp. 137162.

Jackson J. R. (1963), Jobshop-like queueing system, Managemnet science, Vol. 10: pp. 518-521.

Jain, A. K., and Elmaraghy, H. A., 1997. Production scheduling/rescheduling in flexible manufacturing. International Journal of Production Research, 35, 281-309.

Jang, W., (2002), Dynamic scheduling of stochastic jobs on a single machine, European Journal of Operational Research, Vol. 138: pp. 518-530.

Jensen, M. T. (2001), Improving robustness and flexibility of tardiness and total flow-time job shops using robustness measures, Applied Soft Computing, Vol. 1: pp. 35-52.

Jensen, J. (1999) Introduction to Computer Simulation and the Simulation Process, A Guide to Business Decision-Making Using Visual SLAM II and AweSim

Jordan, C. (1996), Batching and Scheduling, Springer.

Kacem, I.., Hammadi, S., and Borne P. (2002), Pareto-optimality approaches for flexible job-shop scheduling problems - hybridization of evolutionary algorithms and fuzzy logic. Mathematics and Computers in Simulation, Vol. 60: pp. 245-276.

Kamaruddin, S. and Duffill, A. W. (2001), Dynamic Scheduling - a knowledge-based system (KBS) approach, Proceeding of the Seventeenth National Confrence on Manufacturing Research, pp 287-292

Karatza, Helen D. (2000), A Comparative of Scheduling Policies in a Distributed system Using Simulation, International Journal of Simulation, Vol. 1(1-2): pp. 12-20.

Kempf, Karl G., "Intelligently scheduling semiconductor wafer fabrication," in Intelligent Scheduling, M. Zweben and M.S. Fox, eds., Morgan Kaufmann Publishers, San Francisco, 1994.

Kim and Kim, 1994, Simulation based real time scheduling in a flexible manufacturing system, Journal of Manufacturing System, Vol. 13(2), pp. 85-93.

Kimms, A. (1997), Multi-level Lot Sizing and Scheduling, ,Physica-Verlag.

Kiran, A. S., and Smith, M. L. (1984), Simulation studies in Job Shop Scheduling - I A Survey. Computing \& Industrial Engineering, Vol. 8: pp. 87-93.

Kiran, A. S., and Smith, M. L. (1984), Simulation studies in Job Shop Scheduling II Performance of priority rules. Computing \& Industrial Engineering, Vol. 8: pp. 95-105.

Kumar, P.R., "Scheduling manufacturing systems of re-entrant lines," in Stochastic Modeling and Analysis of Manufacturing Systems, David D. Yao, ed., pages 325-360, Springer-Verlag, New York, 1994

Kuroda, M. and Wang Z. (1996), Fuzzy job shop scheduling. Int. J. Production Economics, Vol. 44: pp. 45-51.

Lee, C. Y., Lei, L. and Pinedo, M. (1997), Current trends in deterministic scheduling, Annals of Operations Research, Vol. 70: pp. 1-41.

Lee, I., and Shaw, M. J. (2000), A neural-net approach to real time flow-shop sequencing, Computers \& Industrial Engineering, Vol. 38: pp. 125-147.

Lengyel, A., Hatono, I., and Ueda K., (2003), Scheduling for on-time completion in job shops using feasibility function, Computers \& Industrial Engineering, Vol. 45: pp. 215-229.

Li, et. al. (2000), A production rescheduling expert simulation system. European Journal of Operational Research, Vol. 124: pp. 283-293.

Li, Y. C. E., Shaw, Jr. and Martin-Vega, L-A., (1996), Flow-time Performance of Modified Scheduling Heuristics in a Dynamic Rescheduling Environment, Computers ind. Engng, Vol. 31(1/2), 213-216

Li, Y. C. E. and Wade H. Shaw, (1998), Simulation modeling of a dynamic job shop rescheduling with machine availability constraints, Computers ind. Engng, Vol., 35(1-2), . pp. 117-120.

Liu, S.Q., Ong, H.L. and Ng, H.L. (2005), Metaheuristics for minimizing the makespan of the dynamic shop scheduling problem, Advances in Engineering Software, Vol. 36, pp. 199-205

Luh, Peter B., Chen, Dong, and Thakur, Lakshman S. (1999), An Effective Approach for Job-Shop Scheduling with Uncertain Processing Requirements, IEEE Transactions on Robotics and Automation, Vol.15(2): pp. 328-339.

Madureira, A. and Ramos, C., (2001), A New Framework for Deterministic Job-shop Scheduling problems Using Genetic Algorithms, Dept. de Engenharia Informatica, Instituto Superior de Engenharia do Porto, Protugal.

Maturana, F. et al. (1997), Object-oriented job-shop scheduling using genetic algorithms, Computers in Industry, Vol. 32: pp. 281-294.

Mehta, A. (2000) Smart Modeling-Basic Methodology and Advanced Tools, Proceeding of the 2000 Winter Simulation Conference: pp. 241-245.

Mokotoff, E. (2001), Parallel Machine Scheduling Problems: A Survey, Asia-Pacific Journal of Operation Research, Vol. 18: pp. 193-242.

Muhleman, A.P., Lockett, A.G., Farn, C.K., (1982). Job shopscheduling heuristics and frequency of scheduling. International Journal of Production Research. Vol. 20 (2), pp. 227-241.

Nagar, A., Haddock, J. and Heragu, S. (1995), Multiple and Bicriteria Scheduling: A Literature Survey, European Journal of Operation Research, Vol. 81: pp. 88-104.

Olumolade, M. O., and Norrie, D. H., 1996. Reactive scheduling system for cellular manufacturing with failure-prone machines. International Journal of Computer Integrated Manufacturing., 9, 2, 131-144.

Panwalker, S.S., (1977). A survey of scheduling rules. Operations Research 25, 4561.

Pendharkar, P.C., (1999), A computational study on design and performance issues of multi-agent intelligent systems for dynamic scheduling environments, Expert Systems with Applications, Vol. 16. pp. 121-133.

Parka, Y., Kima, S., and Lee, Y-H. (2000), Jobs on parallel machines applying neural network and heuristic rules, Computers \& Industrial Engineering, Vol. 38: pp. 189-202.

Pichitlamken, J., and Nelson, B. L. (2001), Selection-of-the-Best Procedures for Optimization via Simulation, Proceeding of the 2001 Winter Simulation Conference: pp. 401-407.

Pinedo, M. (2002), Scheduling: Theory, Algorithm, and System, $2^{\text {nd. }}$ Ed. Englewood Cliffs, New Jersey. Prentice Hall,

Raheja, A. S., and Subramaniam, V. (2002), Reactive Recovery of Job Shop Schedules - A Survey. The International Journal of Advanced Manufacturing Technology, Vol. 19: pp. 756-763.

Ramashes, R. (1990) Dynamic Job Shop Scheduling: A Survey of Simulation Research. OMEGA, Vol. 18: pp. 43-57.

Rangsaritratsameea,R., Ferrell, W. G.Jr., and Kurz, M. B., 2004, Dynamic rescheduling that simultaneously considers efficiency and stability, Computers \& Industrial Engineering, Vol. 46, pp. 1-15

Rardin, R. E., (1998), Optimization in Operation Research, New Jersey: Prentice Hall,

Rinooy Kan, A. H. G. (1979), Machine Scheduling Problems: Classification, Complexity and Computation. Martinus Nijhoff, The Hague.

Sabuncuoglu, I. and Karabuk,S., (1999), Rescheduling Frequency in an FMS with Uncertain Processing Times and Unreliable Machines, Journal of Mfg. Systems, Vol. 18(4), pp. 268-283.

Sabuncuoglu, I., and Gurgun, B., (1996), A neural network model for scheduling problems, European Journal of Operational Research, Vol. 93 , pp. 288299.

Sabuncuoglu, I. and Bayõz,M. (2000), Analysis of reactive scheduling problems in a job shop environment. European Journal of Operational Research, Vol. 126: pp. 567-586.

Sadeh, N., and Fox, M. S. (1996), Variable and value ordering heuristics for the job shop scheduling constraint satisfaction problem. Artificial Intelligence, pp. 86

Sen, T., and Gupta, S. K. (1984), A state-of-the-art survey of static scheduling research involving due dates, OMEGA, Vol. 12: pp 63-76.

Schmidt, J. W. (1986), Introduction to System Analysis, Modeling and Simulation, Proceedings of the 1986 Winter Simulation Conference: pp. 516.Sevastjanov, S. V. (1994), On Some Geometric Method in Scheduling Theory: A Survey. Discrete Applied Mathematics, Vol. 55: pp. 59-82.

Shafaei, R., and Brunn, P., 1999. Workshop scheduling using practical (inaccurate) data - Part 1: The performance of heuristic scheduling rules in a dynamic job shop environment using a rolling time horizon approach. International Journal of Production Research, 37, 17, 3913-3925.

Sivazlian, B. D. (1975), Optimization Techniques in Operation Research. Englewood Cliff, New Jersey: Prentice Hall, Inc.

Song, D. P., Hicks, C. and Earl, C. F., 2001, Dynamic production scheduling and rescheduling for complex assemblies, Dept. of Earth science and engineering, royal school of mines, UK, pp. 1-16

Sursesh, V., and Chauduri, D. (1993), Dynamic Scheduling - A survey of research, International Journal of Production Economics, Vol. 32: pp. 53-66.

Sun, J., and Xue, D., 2001, A dynamic reactive scheduling mechanism for responding to changes of poduction orders and manufacturing resources, Computers in Industry, Vol. 46, pp. 189-207
V. Subramaniam, T. Ramesh, G. K. Lee, Y. S. Wong and G. S. Hong, (2000) Job Shop Scheduling with Dynamic Fuzzy Selection of Dispatching Rules, In.t J Adv Manufacturing Technology. Vol. 16, pp.759-764.

Vieira G. E., Herrmann, J. W., and Lin, E., (2000), Predicting the Performance of Rescheduling Strategies for Parallel Machine Systems, Journal of Manufacturing Systems, Vol. 19(4),pp. 256-266.

Vieira G. E., Herrmann, J. W., and Lin, E., (2001), Rescheduling manufacturing systems: a framework of strategies, policies, and methods, Department of Mechanical Engineering University of Maryland, pp. 1-39

Watanabe, T., Tokumaru, H., and Hashimoto, Y., (2003), Job-shop scheduling using neural networks, Department of Computer Science and Systems Engineering, Ritsumeikan University, Kyoto 603-77, Japan

Watatani, Y., and Fujii, S., 1992. A study on rescheduling policy in production system. JAPAN/USA Symposium on Flexible Automation, Vol.2, ASME.

Weeks, J. K., and Fryer, J. S. (1976), A simulation study of operating policies in a hypothetical dual-constrained job shop. Management Science, Vol. 22: pp. 1362-1370.

Wu, S. D., Storer, R. H., and Chang, P. -C., 1993. One-machine rescheduling heuristics with efficiency and stability as criteria. Computers \& Operations Research, 20, 1-14.

Yamamoto, M., Nof, S.Y., 1985. Scheduling in the manufacturing operating system environment. International Journal of Production Research, Vol. 23 (4), pp. 705-722.

Yang, S. and Wang D. (2001), A new adaptive neural network and heuristics hybrid approach for job-shop scheduling, Computers \& Operations Research, Vol. 28: pp. 955-971.

Ying, C. C. (1996), Specification of a job shop scheduling simulation model and some properties of its internal transition function, Computers \& Industrial Engineering, Vol. 31(1-2): pp. 201-204.

Yu, H., and Liang, W., (2001), Neural Network and Genetic Algorithm-based hybrid approach to expanded job-shop scheduling, Computer \& industrial Engineering, Vol. 39, pp. 337-356

## APPENDIX A <br> Most Common Scheduling Rules

## 1. Job Scheduling Rules

| EDD | Earliest Due Dates |  |
| :--- | :--- | :--- |
| EDF | Earliest Deadline First |  |
| FASFO | First At Shop First Out |  |
| FCFS | First Come First Served |  |
| FIFO | First In First Out |  |
| FRO | Fewest number of Remaining Opertion |  |
| LDT | Longest SIO/TP ratio |  |
| LIO | Longest Imminent Operation time |  |
| LLF | Least Laxity First (Laxity =kelemahan) |  |
| LMT | Longest SIO.TP Multiplication Time |  |
| LPT | Longest Processing Time |  |
| LRPT | Longest Remaining Processing Time |  |
| MRO | Largest number of Remaining Opertion |  |
| SDT | Shortest SIO/TP ratio |  |
| SIO | Shortest Imminent Operation time (Imminent <br> gilirannya) |  |
| SMT | Shortes SIO.TP Multiplication Time |  |
| SPT | Shortest Processing Time |  |
| SRPT | Shortest Remaining Processing Time |  |

## 2. Machine Scheduling Rules

| FAFS | First Arrived First Served |
| :--- | :--- |
| FCFS | First Come First Served |
| FOPNR | Fewest number of operation remaining |
| LPT. TOT | Largest value of operation time multiplied by total operation time |
| LPT/TOT | Largest value of operation time divided by total operation time |
| LWKR | Least work remaining |
| MOPNR | Most number of operation remaining |
| MWKR | Most work remaining |
| RANDOM | Job priority is random |
| SPT | Shortest Processing Time |
| SPT. TOT | Smallest value of operation time multiplied by total operation <br> time |
| SPT/TOT | Smallest value of operation time divided by total operation time |

## APPENDIX B <br> FIFO, SPT and EDD Algorithm



## FIFO Algorithm




EDD Algorithm

## Appendix C <br> Most Common Performance Measure

1. Time-based measure

| Mean and variance of flow time per job |
| :--- |
| Mean and variance of flow time per operation |
| Mean waiting time |
| Mean idle time |

2. WIP Measure

Average number of job in queue
Average number of operation in queue
Value of work-in-process
3. Due-date related measure

| Mean tardiness |
| :--- |
| Conditional mean tardiness |
| Proportional of job tardy |
| Mean lateness |
| Number of job tardy |
| Maximum lateness |

4. Cost-based Measure

| Cost of idle machines |
| :--- |
| Cost of long promises |
| Cost of carrying work-in-process |
| Total cost per job |
| Average value added in queue |

## Summary for Replication 1 of 20

TALLY VARIABLES


## Summary for Replication 2 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Obser | ations |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 43.471 | (Insuf) | 34.205 | 53.678 | 13 |  |
| Part 2.TotalTime | 53.782 | (Insuf) | 40.000 | 69.708 | 16 |  |
| Part 3.TotalTime | 54.586 | (Insuf) | 42.759 | 65.375 | 23 |  |
| Part 4.TotalTime | 52.760 | (Insuf) | 43.117 | 63.467 | 11 |  |
| Part 5.TotalTime | 51.633 | (Insuf) | 39.000 | 66.107 | 23 |  |
| Part 6.TotalTime | 52.602 | (Insuf) | 39.857 | 63.483 | 13 |  |
| DISCRETE-CHANGE VARIABLES Average Half Width Minimum Maximum Final Value |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| Machine 1.Utilization | . 37827 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 32133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 34000 | 0 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 24439 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 43815 | 5 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 46094 | 4 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01909 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 07785 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 1.Queue.NumberIn | Queue | . 03907 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberIn | Queue | . 10183 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 05406 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.NumberIn | Queue | . 04337 | (Insuf) | . 00000 | 1.0000 | . 00000 |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 13.000 |
| :--- | :--- |
| Part 2.NumberOut | 16.000 |
| Part 3. NumberOut | 23.000 |
| Part 4.NumberOut | 11.000 |
| Part 5. NumberOut | 23.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication 3 of 20

TALLY VARIABLES


## Summary for Replication 4 of 20

| TALLY VARIABLES |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Identifier | Average | Half Width | Minimum | Maximum | Observations |
|  |  |  |  |  |  |
| Part 1.TotalTime | 42.149 | (Insuf) | 35.721 | 59.240 | 12 |
| Part 2.TotalTime | 56.313 | (Insuf) | 44.000 | 69.257 | 17 |
| Part 3.TotalTime | 54.428 | (Insuf) | 44.591 | 78.107 | 11 |
| Part 4.TotalTime | 49.989 | (Insuf) | 38.000 | 79.014 | 21 |
| Part 5.TotalTime | 52.022 | (Insuf) | 43.000 | 62.000 | 31 |
| Part 6.TotalTime | 47.344 | (Insuf) | 43.574 | 52.399 | 6 |

## DISCRETE-CHANGE VARIABLES

Identifier $\quad$ Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization . 34354 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Machine 2.Utilization . 33200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization . 38828 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization . 21989 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization . 45486 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization . 43267 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 1.Queue.NumberlnQueue | . 03092 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberInQueue | . 03590 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue. NumberInQueue | . 04288 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 4.Queue. NumberInQueue | . 01646 | (Insuf) | . 00000 | 1.0000 | 1.0000 |
| Work Station 5.Queue.NumberInQueue | . 08696 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberInQueue | . 06718 | (Insuf) | . 00000 | 2.0000 | . 00000 |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 12.000 |
| :--- | :--- |
| Part 2.NumberOut | 17.000 |
| Part 3. NumberOut | 11.000 |
| Part 4.NumberOut | 21.000 |
| Part 5. NumberOut | 31.000 |
| Part 6.NumberOut | 6.0000 |

## Summary for Replication 5 of $\mathbf{2 0}$

TALLY VARIABLES


## Summary for Replication 6 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 46.840 | (Insuf) | 36.000 | 61.090 | 16 |  |
| Part 2.TotalTime | 52.912 | (Insuf) | 44.000 | 74.149 | 18 |  |
| Part 3.TotalTime | 51.905 | (Insuf) | 40.081 | 78.443 | 13 |  |
| Part 4.TotalTime | 50.142 | (Insuf) | 39.000 | 58.000 | 20 |  |
| Part 5.TotalTime | 52.103 | (Insuf) | 43.000 | 67.537 | 21 |  |
| Part 6.TotalTime | 51.736 | (Insuf) | 43.000 | 66.443 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 33533 | $3^{--}$(Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 32284 | 4 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 34785 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 25400 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 45409 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 45831 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02841 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 08647 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 03155 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberlnQ | Queue | . 08414 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberlnQ | Queue | . 03741 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 05022 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 16.000 |
| :--- | :--- |
| Part 2.NumberOut | 18.000 |
| Part 3.NumberOut | 13.000 |
| Part 4.NumberOut | 20.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication 7 of 20

tally Variables


## Summary for Replication 8 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $44.06 \overline{5}$ | (Insuf) | $38 . \overline{724}$ | 50.990 |
| :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 56.065 | (Insuf) | 40.000 | 71.863 |
| Part 3.TotalTime | 52.623 | (Insuf) | 42.323 | 65.143 |
| Part 4.TotalTime | 51.093 | (Insuf) | 41.000 | 67.853 |
| Part 5.TotalTime | 51.676 | (Insuf) | 39.000 | 64.773 |
| Part 6.TotalTime | 52.471 | (Insuf) | 38.000 | 71.564 |

## DISCRETE-CHANGE VARIABLES

Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .37600 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .30728 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .30369 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | .25891 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .41887 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .50851 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | .02703 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .05953 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .03808 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .12609 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .02076 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .05978 | (Insuf) | .00000 | 2.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 14.000 |
| :--- | :--- |
| Part 2. NumberOut | 13.000 |
| Part 3 NumberOut | 17.000 |
| Part 4.NumberOut | 19.000 |
| Part 5.NumberOut | 17.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 9 of 20

TALLY VARIABLES

| Identifier | Average Half Width Minimum |  |  | Maximum | Observations |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 44.743 | (Insuf) | 34.000 | 57.046 | 16 |  |  |
| Part 2.TotalTime | 55.378 | (Insuf) | 44.720 | 65.000 | 17 |  |  |
| Part 3.TotalTime | 58.213 | (Insuf) | 48.889 | 70.535 | 14 |  |  |
| Part 4.TotalTime | 51.248 | (Insuf) | 43.000 | 67.124 | 20 |  |  |
| Part 5.TotalTime | 52.046 | (Insuf) | 40.011 | 83.620 | 14 |  |  |
| Part 6.TotalTime | 57.227 | (Insuf) | 41.485 | 79.162 | 17 |  |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |  |
| Machine 1.Utilization | . 38133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 2.Utilization | . 34068 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 3.Utilization | . 32195 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 4.Utilization | . 25133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 5.Utilization | . 41269 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 6.Utilization | . 49040 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Work Station 4.Queue.Numberln | Queue | . 01311 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 5.Queue.Numberln | Queue | . 07497 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 1.Queue.Numberln | Queue | . 03333 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 6.Queue.Numberln | Queue | . 14270 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 2.Queue.Numberln | Queue | . 05729 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 3.Queue.Numberln | Queue | . 05181 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| OUTPUTS |  |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |  |
| Part 1.NumberOut | 16.000 |  |  |  |  |  |  |
| Part 2.NumberOut | 17.000 |  |  |  |  |  |  |
| Part 3.NumberOut | 14.000 |  |  |  |  |  |  |
| Part 4.NumberOut | 20.000 |  |  |  |  |  |  |
| Part 5.NumberOut | 14.000 |  |  |  |  |  |  |
| Part 6.NumberOut | 17.000 |  |  |  |  |  |  |

## Summary for Replication 10 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 44.609 | (Insuf) | 34.864 | 51.930 | 19 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 55.302 | (Insuf) | 40.000 | 78.835 | 19 |
| Part 3.TotalTime | 51.385 | (Insuf) | 39.804 | 68.259 | 20 |
| Part 4.TotalTime | 50.883 | (Insuf) | 41.000 | 61.283 | 14 |
| Part 5.TotalTime | 59.707 | (Insuf) | 39.000 | 79.342 | 16 |
| Part 6.TotalTime | 48.874 | (Insuf) | 38.551 | 57.930 | 12 |

DISCRETE-CHANGE VARIABLES
Identifier $\quad$ Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization . 36241 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Machine 2.Utilization . 34647 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization . 31200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization . 24533 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization . 43867 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization . 48600 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | . 02246 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.NumberInQueue | . 07250 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.NumberInQueue | . 03327 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberInQueue | . 12171 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 2.Queue.NumberInQueue | . 04849 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.NumberInQueue | . 02542 | (Insuf) | . 00000 | 1.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 19.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3.NumberOut | 20.000 |
| Part 4.NumberOut | 14.000 |
| Part 5.NumberOut | 16.000 |
| Part 6.NumberOut | 12.000 |

## Summary for Replication 11 of 20

TALLY VARIABLES


## Summary for Replication 12 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 45.093 | (Insuf) | 34.000 | 54.176 | 11 |  |
| Part 2.TotalTime | 55.347 | (Insuf) | 44.000 | 66.726 | 19 |  |
| Part 3.TotalTime | 53.394 | (Insuf) | 41.819 | 69.420 | 19 |  |
| Part 4.TotalTime | 51.236 | (Insuf) | 43.000 | 63.858 | 14 |  |
| Part 5.TotalTime | 52.649 | (Insuf) | 39.000 | 64.106 | 21 |  |
| Part 6.TotalTime | 55.998 | (Insuf) | 46.729 | 63.776 | 18 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final | alue |
| Machine 1.Utilization | . 41006 | $6^{--}$(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 33133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 37200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 23999 | 9 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 45134 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 48873 | 3 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01801 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 08041 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 02638 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberlnQ | Queue | . 12074 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberlnQ | Queue | . 03427 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06846 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 11.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3.NumberOut | 19.000 |
| Part 4.NumberOut | 14.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 18.000 |

## Summary for Replication 13 of 20

TALLY VARIABLES

| Identifier | Average H | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 45.816 | (Insuf) | 34.000 | 57.480 | 14 |  |
| Part 2.TotalTime | 56.326 | (Insuf) | 40.000 | 76.677 | 24 |  |
| Part 3.TotalTime | 54.848 | (Insuf) | 42.234 | 72.402 | 17 |  |
| Part 4.TotalTime | 52.772 | (Insuf) | 46.000 | 66.438 | 17 |  |
| Part 5.TotalTime | 53.018 | (Insuf) | 43.000 | 72.502 | 16 |  |
| Part 6.TotalTime | 56.647 | (Insuf) | 45.809 | 73.649 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average H | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 38480 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 34340 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | . 32715 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 26467 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 44133 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 49978 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02417 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 09296 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.NumberIn | Queue | . 03393 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 11763 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 02511 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 3.Queue.NumberIn | Queue | . 08304 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 14.000 |  |  |  |  |  |
| Part 2.NumberOut | 24.000 |  |  |  |  |  |
| Part 3.NumberOut | 17.000 |  |  |  |  |  |
| Part 4.NumberOut | 17.000 |  |  |  |  |  |
| Part 5.NumberOut | 16.000 |  |  |  |  |  |
| Part 6.NumberOut | 13.000 |  |  |  |  |  |

## Summary for Replication 14 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 43.020 | (Insuf) | 35.214 | 50.325 | 10 |  |
| Part 2.TotalTime | 56.413 | (Insuf) | 40.000 | 71.468 | 19 |  |
| Part 3.TotalTime | 55.854 | (Insuf) | 43.021 | 78.827 | 22 |  |
| Part 4.TotalTime | 52.771 | (Insuf) | 43.000 | 66.191 | 17 |  |
| Part 5.TotalTime | 53.366 | (Insuf) | 39.000 | 66.988 | 21 |  |
| Part 6.TotalTime | 52.771 | (Insuf) | 38.159 | 63.565 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final | alue |
| Machine 1.Utilization | . 37467 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 33000 | 0 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 37261 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 23200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 45184 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 51333 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 1.Queue.Numberln | Queue | . 03259 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 03889 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06971 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 4.Queue.NumberlnQ | Queue | . 02176 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 09070 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 12943 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 10.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3.NumberOut | 22.000 |
| Part 4.NumberOut | 17.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication 15 of 20

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 44.941 | (Insuf) | 36.000 | 51.215 | 12 |  |
| Part 2.TotalTime | 57.493 | (Insuf) | 42.000 | 74.713 | 27 |  |
| Part 3.TotalTime | 54.500 | (Insuf) | 44.059 | 62.346 | 9 |  |
| Part 4.TotalTime | 51.165 | (Insuf) | 39.000 | 64.912 | 18 |  |
| Part 5.TotalTime | 58.901 | (Insuf) | 42.000 | 75.720 | 15 |  |
| Part 6.TotalTime | 57.448 | (Insuf) | 41.367 | 70.292 | 19 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 39930 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 33772 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 31467 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 25733 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 46263 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 50702 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02292 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 11213 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 03578 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 15658 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 01613 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06775 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 12.000 |  |  |  |  |  |
| Part 2.NumberOut | 27.000 |  |  |  |  |  |
| Part 3.NumberOut | 9.0000 |  |  |  |  |  |
| Part 4.NumberOut | 18.000 |  |  |  |  |  |
| Part 5.NumberOut | 15.000 |  |  |  |  |  |
| Part 6.NumberOut | 19.000 |  |  |  |  |  |

## Summary for Replication 16 of 20

TALLY VARI ABLES

| Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 41.992 | (Insuf) | 34.000 | 52.852 | 16 |  |
| Part 2.TotalTime | 55.347 | (Insuf) | 44.557 | 78.018 | 14 |  |
| Part 3.TotalTime | 51.950 | (Insuf) | 41.181 | 76.276 | 15 |  |
| Part 4.TotalTime | 52.089 | (Insuf) | 45.861 | 66.479 | 16 |  |
| Part 5.TotalTime | 53.664 | (Insuf) | 44.000 | 75.000 | 19 |  |
| Part 6.TotalTime | 53.779 | (Insuf) | 40.313 | 67.051 | 20 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average Half Width |  | Minimum | Maximum | Final Value |  |
| Machine 1.Utilization | . 36038 | ${ }^{---}$(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 31867 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 32117 | 7 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 23800 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 42657 | 7 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 47133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.NumberIn | Queue | . 01166 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 06206 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 04238 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 15366 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 04427 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06129 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 16.000 |
| :--- | :--- |
| Part 2.NumberOut | 14.000 |
| Part 3.NumberOut | 15.000 |
| Part 4.NumberOut | 16.000 |
| Part 5.NumberOut | 19.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 17 of 20

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 47.011 | (Insuf) | 34.234 | 63.573 | 9 |  |
| Part 2.TotalTime | 53.503 | (Insuf) | 39.562 | 65.965 | 14 |  |
| Part 3.TotalTime | 50.816 | (Insuf) | 39.000 | 71.377 | 18 |  |
| Part 4.TotalTime | 51.273 | (Insuf) | 39.296 | 61.607 | 22 |  |
| Part 5.TotalTime | 54.766 | (Insuf) | 43.126 | 64.214 | 21 |  |
| Part 6.TotalTime | 53.550 | (Insuf) | 42.561 | 68.697 | 17 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 39917 | $7{ }^{\text {(Insuf) }}$ | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 31915 | 15 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 35318 | 8 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 22867 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 43954 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 50724 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01429 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 07393 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 02814 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 11765 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 04381 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 08176 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 9.0000 |  |  |  |  |  |
| Part 2.Numberln | 15.000 |  |  |  |  |  |
| Part 2.NumberOut | 14.000 |  |  |  |  |  |
| Part 3.NumberOut | 18.000 |  |  |  |  |  |
| Part 4.NumberOut | 22.000 |  |  |  |  |  |
| Part 5.NumberOut | 21.000 |  |  |  |  |  |
| Part 6.NumberOut | 17.000 |  |  |  |  |  |

## Summary for Replication 18 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $46.35 \overline{1}$ | (Insuf) | 34.000 | 55.769 | 15 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 55.154 | (Insuf) | 44.000 | 72.506 | 17 |
| Part 3.TotalTime | 51.494 | (Insuf) | 41.000 | 64.768 | 20 |
| Part 4.TotalTime | 51.949 | (Insuf) | 40.292 | 65.791 | 18 |
| Part 5.TotalTime | 58.042 | (Insuf) | 39.000 | 88.603 | 13 |
| Part 6.TotalTime | 52.399 | (Insuf) | 37.970 | 67.863 | 19 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .38267 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .32781 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | .31445 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .24723 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | .42778 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 6.Utilization | .50333 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .03439 | (Insuf) | .00000 | 2.0000 | 1.0000 |  |
| Work Station 5.Queue.NumberInQueue | .05171 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .03522 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .15524 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .03218 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .07265 | (Insuf) | .00000 | 2.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 15.000 |
| :--- | :--- |
| Part 2.NumberOut | 17.000 |
| Part 3.NumberOut | 20.000 |
| Part 4.NumberOut | 18.000 |
| Part 5.NumberOut | 13.000 |
| Part 6.NumberOut | 19.000 |

## Summary for Replication 19 of 20

TALLY VARIABLES


## Summary for Replication 20 of 20

tally variables
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $43.85 \overline{6}$ | (Insuf) | $\overline{3} \overline{3} .349$ | $54.38 \overline{4}$ |
| :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 54.351 | (Insuf) | 45.000 | 60.594 |
| Part 3.TotalTime | 51.816 | (Insuf) | 43.000 | 72.026 |
| Part 4.TotalTime | 50.888 | (Insuf) | 39.000 | 77.076 |
| Part 5.TotalTime | 53.095 | (Insuf) | 44.800 | 68.046 |
| Part 6.TotalTime | 54.813 | (Insuf) | 43.829 | 74.311 |


| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Identifier | Average | Half Width | Minimum | Maximum | Final Value |  |
| Machine 1.Utilization | .33594 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | .33400 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .33800 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .24867 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .44803 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .45667 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .02776 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .06092 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 1.Queue.NumberInQueue | .02392 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .10219 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .04409 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .07656 | (Insuf) | .00000 | 2.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 15.000 |
| :--- | :--- |
| Part 2.NumberOut | 15.000 |
| Part 3.NumberOut | 13.000 |
| Part 4.NumberOut | 22.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 14.000 |

## Summary for Replication 1 of 20

| TALLY VARIABLES Identifier | Average H | Half Width | Minimum | Maximum | Obser | tions |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 48.081 | (Insuf) | 32.636 | 64.711 | 21 |  |
| Part 2.TotalTime | 61.781 | (Insuf) | 49.000 | 81.247 | 24 |  |
| Part 3.TotalTime | 56.961 | (Insuf) | 41.538 | 80.614 | 23 |  |
| Part 4.TotalTime | 56.643 | (Insuf) | 37.558 | 84.507 | 30 |  |
| Part 5.TotalTime | 61.968 | (Insuf) | 47.000 | 80.000 | 26 |  |
| Part 6.TotalTime | 54.669 | (Insuf) | 44.309 | 83.650 | 27 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 57577 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 47333 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 43444 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 37068 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 64377 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 67310 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue. NumberInQueue |  | . 08105 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 5.Queue.NumberInQueue |  | . 21839 | (Insuf) | . 00000 | 3.0000 | 1.0000 |
| Work Station 1.Queue.NumberInQueue |  | . 09901 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberInQueue |  | . 44552 | (Insuf) | . 00000 | 4.0000 | . 00000 |
| Work Station 2.Queue.NumberInQueue |  | . 13939 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 3.Queue. NumberInQueue |  | . 11514 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 21.000 |  |  |  |  |  |
| Part 2.NumberOut | 24.000 |  |  |  |  |  |
| Part 3.NumberOut | 23.000 |  |  |  |  |  |
| Part 4.NumberOut | 30.000 |  |  |  |  |  |
| Part 5.NumberOut | 26.000 |  |  |  |  |  |
| Part 6.NumberOut | 27.000 |  |  |  |  |  |

## Summary for Replication 2 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $\mathbf{4 7 . 0 1 5}$ | (Insuf) | $3 \overline{3} .000$ | 58.313 |
| :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 60.420 | (Insuf) | 43.000 | 86.195 |
| Part 3.TotalTime | 57.586 | (Insuf) | 41.869 | 79.787 |
| Part 4.TotalTime | 59.309 | (Insuf) | 43.444 | 75.420 |
| Part 5.TotalTime | 58.200 | (Insuf) | 42.000 | 83.603 |
| Part 6.TotalTime | 60.720 | (Insuf) | 36.034 | 82.638 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .55102 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .46133 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .48133 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .34215 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | .65536 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 6.Utilization | .67368 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | .06004 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .31365 | (Insuf) | .00000 | 4.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .12775 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .38306 | (Insuf) | .00000 | 3.0000 | 1.0000 |  |
| Work Station 2.Queue.NumberInQueue | .13461 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .18582 | (Insuf) | .00000 | 3.0000 | .00000 |  |

OUTPUTS
Identifier
Value

| Part 1.NumberOut | 19.000 |
| :--- | :--- |
| Part 2.NumberOut | 25.000 |
| Part 3.NumberOut | 32.000 |
| Part 4.NumberOut | 20.000 |
| Part 5.NumberOut | 30.000 |
| Part 6.NumberOut | 22.000 |

## Summary for Replication $\mathbf{3}$ of $\mathbf{2 0}$

TALLY VARIABLES


TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $48.53 \overline{9}$ | (Insuf) | 31.000 | 64.943 | 18 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 59.479 | (Insuf) | 44.004 | 82.499 | 32 |
| Part 3.TotalTime | 58.802 | (Insuf) | 37.963 | 72.672 | 16 |
| Part 4.TotalTime | 59.553 | (Insuf) | 40.000 | 83.752 | 39 |
| Part 5.TotalTime | 58.796 | (Insuf) | 44.000 | 81.693 | 38 |
| Part 6.TotalTime | 65.598 | (Insuf) | 48.552 | 106.76 | 9 |

## DISCRETE-CHANGE VARIABLES

Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .50904 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .52770 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .52000 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .33467 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .71604 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .66025 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | .05496 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .32042 | (Insuf) | .00000 | 3.0000 | 2.0000 |  |
| Work Station 1.Queue.NumberInQueue | .09318 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .31661 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .16840 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .24512 | (Insuf) | .00000 | 3.0000 | .00000 |  |

OUTPUTS
Identifier
Value

| Part 1.NumberOut | 18.000 |
| :--- | :--- |
| Part 2.NumberOut | 32.000 |
| Part 3.NumberOut | 16.000 |
| Part 4.NumberOut | 39.000 |
| Part 5.NumberOut | 38.000 |
| Part 6.NumberOut | 9.0000 |

## Summary for Replication 5 of $\mathbf{2 0}$

TALLY VARIABLES


## Summary for Replication 6 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 49.244 | (Insuf) | 36.198 | 63.332 | 28 |  |
| Part 2.TotalTime | 61.740 | (Insuf) | 43.003 | 75.773 | 31 |  |
| Part 3.TotalTime | 66.280 | (Insuf) | 49.119 | 94.495 | 16 |  |
| Part 4.TotalTime | 56.122 | (Insuf) | 40.000 | 77.569 | 31 |  |
| Part 5.TotalTime | 58.001 | (Insuf) | 42.728 | 89.376 | 29 |  |
| Part 6.TotalTime | 63.918 | (Insuf) | 37.152 | 94.542 | 20 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 55643 | $3^{--}$(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 52156 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | . 44733 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 38748 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 68067 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 66602 | 2 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 1.Queue.Numberln | Queue | . 13514 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 17216 | (Insuf) | . 00000 | 3.0000 | 1.0000 |
| Work Station 3.Queue.Numberln | Queue | . 18505 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 4.Queue.NumberlnQ | Queue | . 08265 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.NumberlnQ | Queue | . 34975 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 42096 | (Insuf) | . 00000 | 3.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 28.000 |
| :--- | :--- |
| Part 2.NumberOut | 31.000 |
| Part 3. NumberOut | 16.000 |
| Part 4.NumberOut | 31.000 |
| Part 5.NumberOut | 29.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 7 of 20

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 46.456 | (Insuf) | 37.370 | 59.237 | 21 |  |
| Part 2.TotalTime | 60.560 | (Insuf) | 41.115 | 79.262 | 19 |  |
| Part 3.TotalTime | 60.067 | (Insuf) | 42.677 | 84.010 | 24 |  |
| Part 4.TotalTime | 56.044 | (Insuf) | 42.000 | 79.702 | 31 |  |
| Part 5.TotalTime | 59.232 | (Insuf) | 39.000 | 81.903 | 30 |  |
| Part 6.TotalTime | 59.831 | (Insuf) | 43.959 | 81.667 | 24 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 50478 | 8 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 47396 | 6 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 47237 | 7 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 33574 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 65596 | 6 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 66041 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 05155 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 25762 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 10347 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 40671 | (Insuf) | . 00000 | 4.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 14992 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.NumberIn | Queue | . 23215 | (Insuf) | . 00000 | 3.0000 | 2.0000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 21.000 |  |  |  |  |  |
| Part 2.NumberOut | 19.000 |  |  |  |  |  |
| Part 3.NumberOut | 24.000 |  |  |  |  |  |
| Part 4.NumberOut | 31.000 |  |  |  |  |  |
| Part 5.NumberOut | 30.000 |  |  |  |  |  |
| Part 6.NumberOut | 24.000 |  |  |  |  |  |

## Summary for Replication 8 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 44.950 | (Insuf) | 31.000 | 60.992 | 20 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 59.821 | (Insuf) | 47.106 | 74.040 | 18 |
| Part 3.TotalTime | 58.642 | (Insuf) | 40.860 | 96.875 | 21 |
| Part 4.TotalTime | 58.671 | (Insuf) | 39.852 | 77.214 | 31 |
| Part 5.TotalTime | 56.871 | (Insuf) | 42.515 | 92.443 | 36 |
| Part 6.TotalTime | 58.975 | (Insuf) | 42.539 | 79.794 | 27 |


| DISCRETE-CHANGE VARIABLES |  |
| :--- | :--- |
| Identifier |  |
| Average Half Width Minimum Maximum Final Value |  |


| Machine 1.Utilization | .53446 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .46516 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | .50267 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .34342 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | .65875 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .66913 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | .05660 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .33752 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .10389 | (Insuf) | .00000 | 2.0000 | 1.0000 |  |
| Work Station 6.Queue.NumberInQueue | .45370 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .09972 | (Insuf) | .00000 | 2.0000 | 1.0000 |  |
| Work Station 3.Queue.NumberInQueue | .18659 | (Insuf) | .00000 | 3.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 20.000 |
| :--- | :--- |
| Part 2.NumberOut | 18.000 |
| Part 3.NumberOut | 21.000 |
| Part 4.NumberOut | 31.000 |
| Part 5.NumberOut | 36.000 |
| Part 6.NumberOut | 27.000 |

## Summary for Replication 9 of $\mathbf{2 0}$

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 44.162 | (Insuf) | 32.715 | 71.365 | 16 |  |
| Part 2.TotalTime | 57.942 | (Insuf) | 39.589 | 84.137 | 31 |  |
| Part 3.TotalTime | 59.978 | (Insuf) | 40.920 | 71.917 | 24 |  |
| Part 4.TotalTime | 60.862 | (Insuf) | 44.990 | 92.812 | 29 |  |
| Part 5.TotalTime | 59.551 | (Insuf) | 42.000 | 79.968 | 29 |  |
| Part 6.TotalTime | 56.387 | (Insuf) | 40.702 | 77.564 | 23 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average H | If Width | Minimum | Maximum | F Final | lue |
| Machine 1.Utilization | . 56475 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 47268 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 47548 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 32267 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 66683 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 69941 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 03244 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 22514 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 11194 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 42076 | (Insuf) | . 00000 | 4.0000 | 2.0000 |
| Work Station 2.Queue.Numberln | Queue | . 13319 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 17693 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 16.000 |  |  |  |  |  |
| Part 2.NumberOut | 31.000 |  |  |  |  |  |
| Part 3.NumberOut | 24.000 |  |  |  |  |  |
| Part 4.NumberOut | 29.000 |  |  |  |  |  |
| Part 5.NumberOut | 29.000 |  |  |  |  |  |
| Part 6.NumberOut | 23.000 |  |  |  |  |  |

## Summary for Replication 10 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 47.900 | (Insuf) | 34.397 | 63.000 | 27 |  |
| Part 2.TotalTime | 62.891 | (Insuf) | 49.438 | 78.749 | 23 |  |
| Part 3.TotalTime | 58.220 | (Insuf) | 45.377 | 81.695 | 23 |  |
| Part 4.TotalTime | 55.295 | (Insuf) | 38.178 | 83.249 | 29 |  |
| Part 5.TotalTime | 62.064 | (Insuf) | 44.010 | 87.170 | 25 |  |
| Part 6.TotalTime | 54.896 | (Insuf) | 32.000 | 75.722 | 24 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 54225 | $5^{---}$(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 47565 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 42867 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 38400 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 64867 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 64437 | 7 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 07976 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 26519 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 10782 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberIn | Queue | . 44979 | (Insuf) | . 00000 | 4.0000 | 2.0000 |
| Work Station 2.Queue.Numberln | Queue | . 17046 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 10382 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 27.000 |
| :--- | :--- |
| Part 2.NumberOut | 23.000 |
| Part 3. NumberOut | 23.000 |
| Part 4.NumberOut | 29.000 |
| Part 5.NumberOut | 25.000 |
| Part 6.NumberOut | 24.000 |

## Summary for Replication 11 of 20

TALLY VARIABLES

| Identifier | Average H | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 49.834 | (Insuf) | 39.169 | 62.737 | 22 |  |
| Part 2.TotalTime | 62.484 | (Insuf) | 43.121 | 90.230 | 26 |  |
| Part 3.TotalTime | 55.907 | (Insuf) | 43.157 | 73.934 | 25 |  |
| Part 4.TotalTime | 57.895 | (Insuf) | 41.412 | 78.354 | 28 |  |
| Part 5.TotalTime | 60.134 | (Insuf) | 44.972 | 75.836 | 19 |  |
| Part 6.TotalTime | 58.279 | (Insuf) | 43.309 | 78.332 | 28 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 57190 | --- | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 46887 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | . 40005 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 37267 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 66370 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 71014 | 4 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.Numberln | Queue | . 08785 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 23852 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 1.Queue.NumberInQ | Queue | . 08398 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 6.Queue.Numberln | Queue | . 49973 | (Insuf) | . 00000 | 4.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 09449 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 10657 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier Value |  |  |  |  |  |  |
| Part 1.NumberOut 22.000 |  |  |  |  |  |  |
| Part 2.NumberOut 26.000 |  |  |  |  |  |  |
| Part 3.NumberOut 25.000 |  |  |  |  |  |  |
| Part 4.NumberOut 28.000 |  |  |  |  |  |  |
| Part 5.NumberOut 19.000 |  |  |  |  |  |  |
| Part 6.NumberOut 28.000 |  |  |  |  |  |  |

## Summary for Replication 12 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 48.790 | (Insuf) | 31.092 | 66.681 | 22 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Part 2.TotalTime | 62.785 | (Insuf) | 41.703 | 91.318 | 25 |
| Part 3.TotalTime | 63.983 | (Insuf) | 42.241 | 90.523 | 28 |
| Part 4.TotalTime | 59.990 | (Insuf) | 40.000 | 87.000 | 23 |
| Part 5.TotalTime | 64.343 | (Insuf) | 40.720 | 93.998 | 34 |
| Part 6.TotalTime | 67.971 | (Insuf) | 38.802 | 98.259 | 25 |

## DISCRETE-CHANGE VARIABLES

Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .58540 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .48459 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | .49252 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | .36200 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .65933 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 6.Utilization | .70273 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 1.Queue.NumberInQueue | .13929 | (Insuf) | .00000 | 2.0000 | 1.0000 |  |
| Work Station 2.Queue.NumberInQueue | .18044 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .29236 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .04785 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .45927 | (Insuf) | .00000 | 4.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .57755 | (Insuf) | .00000 | 5.0000 | .00000 |  |

OUTPUTS
Identifier Value

|  |  |
| :--- | :--- |
| Part 1.NumberOut | 22.000 |
| Part 2.NumberOut | 25.000 |
| Part 3.NumberOut | 28.000 |
| Part 4.NumberOut | 23.000 |
| Part 5.NumberOut | 34.000 |
| Part 6.NumberOut | 25.000 |

## Summary for Replication 13 of 20

TALLY VARIABLES


## Summary for Replication 14 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 47.209 | (Insuf) | 34.159 | 69.653 | 18 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 61.895 | (Insuf) | 40.000 | 76.433 | 25 |  |
| Part 3.TotalTime | 60.220 | (Insuf) | 42.331 | 101.90 | 34 |  |
| Part 4.TotalTime | 56.243 | (Insuf) | 36.994 | 70.541 | 26 |  |
| Part 5.TotalTime | 58.855 | (Insuf) | 42.865 | 83.601 | 31 |  |
| Part 6.TotalTime | 60.543 | (Insuf) | 45.540 | 79.327 | 20 |  |
| Work Station 3.Queue.WaitingTime | 1.6890 |  |  | (Insuf) | .00000 | 11.668 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .55455 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .44333 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .49182 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .35835 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .66061 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 6.Utilization | .64527 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .06124 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .34646 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .12455 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .38138 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .15130 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .16778 | (Insuf) | .00000 | 3.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 18.000 |
| :--- | :--- |
| Part 2.NumberOut | 25.000 |
| Part 3.NumberOut | 34.000 |
| Part 4.NumberOut | 26.000 |
| Part 5.NumberOut | 31.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 15 of 20

TALLY VARIABLES


## Summary for Replication 16 of 20

TALLY VARIABLES

| Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 46.579 | (Insuf) | 33.964 | 66.096 | 21 |  |
| Part 2.TotalTime | 58.533 | (Insuf) | 42.000 | 74.423 | 15 |  |
| Part 3.TotalTime | 60.049 | (Insuf) | 43.670 | 77.689 | 29 |  |
| Part 4.TotalTime | 58.540 | (Insuf) | 43.695 | 84.159 | 32 |  |
| Part 5.TotalTime | 57.578 | (Insuf) | 41.914 | 88.710 | 26 |  |
| Part 6.TotalTime | 56.166 | (Insuf) | 38.531 | 82.596 | 29 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average Half Width |  | Minimum | Maximum | Final Value |  |
| Machine 1.Utilization | . 56391 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 43064 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | . 44600 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 33801 | 11 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 62114 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 67650 | 0 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.Numberln | Queue | . 07397 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 20457 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 13635 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberIn | Queue | . 49765 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 10533 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 3.Queue.Numberln | Queue | . 20500 | (Insuf) | . 00000 | 3.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 21.000 |
| :--- | :--- |
| Part 2.NumberOut | 15.000 |
| Part 3.NumberOut | 29.000 |
| Part 4.NumberOut | 32.000 |
| Part 5.NumberOut | 26.000 |
| Part 6.NumberOut | 29.000 |

## Summary for Replication 17 of 20

TALLY VARIABLES

| Identifier | Average Half Width Minimum |  |  | Maximum | Observations |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 48.920 | (Insuf) | 33.000 | 61.307 | 15 |  |  |
| Part 2.TotalTime | 57.545 | (Insuf) | 37.000 | 77.856 | 22 |  |  |
| Part 3.TotalTime | 59.689 | (Insuf) | 42.000 | 76.166 | 30 |  |  |
| Part 4.TotalTime | 55.812 | (Insuf) | 41.000 | 76.597 | 31 |  |  |
| Part 5.TotalTime | 60.723 | (Insuf) | 42.586 | 79.806 | 31 |  |  |
| Part 6.TotalTime | 59.850 | (Insuf) | 38.147 | 88.150 | 26 |  |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | alue |  |
| Machine 1.Utilization | . 59827 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 2.Utilization | . 46933 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 3.Utilization | . 49098 | 8 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 4.Utilization | . 34267 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 5.Utilization | . 64787 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 6.Utilization | . 70027 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Work Station 4.Queue.Numberln | Queue | . 04890 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 5.Queue.Numberln | Queue | . 25299 | (Insuf) | . 00000 | 3.0000 | 1.0000 |  |
| Work Station 1.Queue.Numberln | Queue | . 09715 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 6.Queue.Numberln | Queue | . 47189 | (Insuf) | . 00000 | 4.0000 | . 00000 |  |
| Work Station 2.Queue.Numberln | Queue | . 17042 | (Insuf) | . 00000 | 3.0000 | . 00000 |  |
| Work Station 3.Queue. Numberln | Queue | . 18656 | (Insuf) | . 00000 | 2.0000 | 1.0000 |  |
| OUTPUTS |  |  |  |  |  |  |  |
| Identifier Value | Value |  |  |  |  |  |  |
| Part 1.NumberOut 15.000 |  |  |  |  |  |  |  |
| Part 2.NumberOut | 22.000 |  |  |  |  |  |  |
| Part 3.NumberOut | 30.000 |  |  |  |  |  |  |
| Part 4.NumberOut | 31.000 |  |  |  |  |  |  |
| Part 5.NumberOut | 31.000 |  |  |  |  |  |  |
| Part 6.NumberOut | 26.000 |  |  |  |  |  |  |

## Summary for Replication 18 of 20

TALLY VARIABLES

| Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 51.183 | (Insuf) | 36.082 | 64.323 | 27 |  |
| Part 2.TotalTime | 60.239 | (Insuf) | 41.088 | 88.864 | 27 |  |
| Part 3.TotalTime | 62.380 | (Insuf) | 42.709 | 76.726 | 29 |  |
| Part 4.TotalTime | 59.870 | (Insuf) | 43.780 | 89.059 | 23 |  |
| Part 5.TotalTime | 60.904 | (Insuf) | 44.313 | 94.629 | 26 |  |
| Part 6.TotalTime | 57.091 | (Insuf) | 44.000 | 75.428 | 23 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average Half Width |  | Minimum | Maximum | Final Value |  |
| Machine 1.Utilization | . 54759 | 9 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 48672 | 2 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 42000 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 39914 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 65292 | 2 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 65292 | 2 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.NumberIn | Queue | . 12875 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 5.Queue.NumberIn | Queue | . 28270 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 13852 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 46506 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 17173 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 11169 | (Insuf) | . 00000 | 3.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 27.000 |
| :--- | :--- |
| Part 2.NumberOut | 27.000 |
| Part 3. NumberOut | 29.000 |
| Part 4.NumberOut | 23.000 |
| Part 5.NumberOut | 26.000 |
| Part 6.NumberOut | 23.000 |

## Summary for Replication 19 of 20

TALLY VARIABLES


## Summary for Replication 20 of 20

tally variables
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $48.00 \overline{1}$ | (Insuf) | 35.000 | 70.650 | 23 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 59.020 | (Insuf) | 42.657 | 78.378 | 22 |
| Part 3.TotalTime | 58.788 | (Insuf) | 38.000 | 90.260 | 17 |
| Part 4.TotalTime | 57.119 | (Insuf) | 43.461 | 82.543 | 33 |
| Part 5.TotalTime | 61.545 | (Insuf) | 43.130 | 88.159 | 33 |
| Part 6.TotalTime | 56.399 | (Insuf) | 33.924 | 73.982 | 26 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .55129 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .48840 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | .47710 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | .33662 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .66530 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .64126 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 1.Queue.NumberInQueue | .11737 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .12153 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .20918 | (Insuf) | .00000 | 3.0000 | 1.0000 |  |
| Work Station 4.Queue.NumberInQueue | .06487 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .31928 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .37998 | (Insuf) | .00000 | 3.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 23.000 |
| :--- | :--- |
| Part 2.NumberOut | 22.000 |
| Part 3.NumberOut | 17.000 |
| Part 4.NumberOut | 33.000 |
| Part 5.NumberOut | 33.000 |
| Part 6.NumberOut | 26.000 |

## Summary for Replication 1 of 20



## Summary for Replication 2 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $43.4 \overline{1}$ | (Insuf) | 34.205 | 53.678 | 13 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 53.782 | (Insuf) | 40.000 | 69.708 | 16 |
| Part 3.TotalTime | 54.586 | (Insuf) | 42.759 | 65.375 | 23 |
| Part 4.TotalTime | 52.760 | (Insuf) | 43.117 | 63.467 | 11 |
| Part 5.TotalTime | 51.633 | (Insuf) | 39.000 | 66.107 | 23 |
| Part 6.TotalTime | 52.602 | (Insuf) | 39.857 | 63.483 | 13 |

## DISCRETE-CHANGE VARIABLES

Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization . 37827 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Machine 2.Utilization . 32133 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization . 34000 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization . 24439 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization . 43815 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization . 46094 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.NumberlnQueue | . 01909 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.NumberInQueue | . 07785 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 1.Queue.NumberlnQueue | . 03907 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberInQueue | . 10183 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberInQueue | . 05406 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.NumberInQueue | . 04337 | (Insuf) | . 00000 | 1.0000 | . 00000 |

## OUTPUTS

dentifier Value

| Part 1.NumberOut | 13.000 |
| :--- | :--- |
| Part 2.NumberOut | 16.000 |
| Part 3.NumberOut | 23.000 |
| Part 4.NumberOut | 11.000 |
| Part 5.NumberOut | 23.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication $\mathbf{3}$ of $\mathbf{2 0}$

TALLY VARIABLES


## Summary for Replication 4 of 20

| TALLY VARIABLES |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Identifier | Average | Half Width | Minimum | Maximum | Observations |
|  |  |  |  |  |  |
| Part 1.TotalTime | 42.149 | (Insuf) | 35.721 | 59.240 | 12 |
| Part 2.TotalTime | 56.313 | (Insuf) | 44.000 | 69.257 | 17 |
| Part 3.TotalTime | 54.428 | (Insuf) | 44.591 | 78.107 | 11 |
| Part 4.TotalTime | 49.989 | (Insuf) | 38.000 | 79.014 | 21 |
| Part 5.TotalTime | 52.022 | (Insuf) | 43.000 | 62.000 | 31 |
| Part 6.TotalTime | 47.344 | (Insuf) | 43.574 | 52.399 | 6 |

## DISCRETE-CHANGE VARIABLES

Identifier Average Half Width Minimum Maximum Final Value


## Summary for Replication 5 of 20

TALLY VARIABLES


## Summary for Replication 6 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 46.840 | (Insuf) | 36.000 | 61.090 | 16 |  |
| Part 2.TotalTime | 52.912 | (Insuf) | 44.000 | 74.149 | 18 |  |
| Part 3.TotalTime | 51.905 | (Insuf) | 40.081 | 78.443 | 13 |  |
| Part 4.TotalTime | 50.142 | (Insuf) | 39.000 | 58.000 | 20 |  |
| Part 5.TotalTime | 52.103 | (Insuf) | 43.000 | 67.537 | 21 |  |
| Part 6.TotalTime | 51.736 | (Insuf) | 43.000 | 66.443 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 33533 | $3^{--}$(Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 32284 | 4 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 34785 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 25400 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 45409 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 45831 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02841 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 08647 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 03155 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberlnQ | Queue | . 08414 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberlnQ | Queue | . 03741 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 05022 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 16.000 |
| :--- | :--- |
| Part 2.NumberOut | 18.000 |
| Part 3.NumberOut | 13.000 |
| Part 4.NumberOut | 20.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication 7 of 20

TALLY VARIABLES


## Summary for Replication 8 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 44.065 | (Insuf) | 38.724 | 50.990 | 14 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 56.065 | (Insuf) | 40.000 | 71.863 | 13 |
| Part 3.TotalTime | 52.623 | (Insuf) | 42.323 | 65.143 | 17 |
| Part 4.TotalTime | 51.093 | (Insuf) | 41.000 | 67.853 | 19 |
| Part 5.TotalTime | 51.676 | (Insuf) | 39.000 | 64.773 | 17 |
| Part 6.TotalTime | 52.471 | (Insuf) | 38.000 | 71.564 | 20 |



OUTPUTS
Identifier Value

| Part 1.NumberOut | 14.000 |
| :--- | :--- |
| Part 2.NumberOut | 13.000 |
| Part 3.NumberOut | 17.000 |
| Part 4.NumberOut | 19.000 |
| Part 5.NumberOut | 17.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 9 of 20

tally Variables

| Identifier | Average Half Width Minimum |  |  | Maximum | Observations |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 44.743 | (Insuf) | 34.000 | 57.046 | 16 |  |  |
| Part 2.TotalTime | 55.378 | (Insuf) | 44.720 | 65.000 | 17 |  |  |
| Part 3.TotalTime | 58.213 | (Insuf) | 48.889 | 70.535 | 14 |  |  |
| Part 4.TotalTime | 51.248 | (Insuf) | 43.000 | 67.124 | 20 |  |  |
| Part 5.TotalTime | 52.046 | (Insuf) | 40.011 | 83.620 | 14 |  |  |
| Part 6.TotalTime | 57.227 | (Insuf) | 41.485 | 79.162 | 17 |  |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | alue |  |
| Machine 1.Utilization | . 38133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 2.Utilization | . 34068 | 8 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 3.Utilization | . 32195 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Machine 4.Utilization | . 25133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 5.Utilization | . 41269 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |  |
| Machine 6.Utilization | . 49040 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |  |
| Work Station 4.Queue.Numberln | Queue | . 01311 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 5.Queue.Numberln | Queue | . 07497 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 1.Queue.Numberln | Queue | . 03333 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 6.Queue.NumberIn | Queue | . 14270 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 2.Queue.Numberln | Queue | . 05729 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| Work Station 3.Queue.Numberln | Queue | . 05181 | (Insuf) | . 00000 | 2.0000 | . 00000 |  |
| OUTPUTS |  |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |  |
| Part 1.NumberOut | 16.000 |  |  |  |  |  |  |
| Part 2.NumberOut | 17.000 |  |  |  |  |  |  |
| Part 3.NumberOut | 14.000 |  |  |  |  |  |  |
| Part 4.NumberOut | 20.000 |  |  |  |  |  |  |
| Part 5.NumberOut | 14.000 |  |  |  |  |  |  |
| Part 6.NumberOut | 17.000 |  |  |  |  |  |  |

## Summary for Replication 10 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | 44.609 | (Insuf) | 34.864 | 51.930 | 19 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 55.302 | (Insuf) | 40.000 | 78.835 | 19 |
| Part 3.TotalTime | 51.385 | (Insuf) | 39.804 | 68.259 | 20 |
| Part 4.TotalTime | 50.883 | (Insuf) | 41.000 | 61.283 | 14 |
| Part 5.TotalTime | 59.707 | (Insuf) | 39.000 | 79.342 | 16 |
| Part 6.TotalTime | 48.874 | (Insuf) | 38.551 | 57.930 | 12 |

DISCRETE-CHANGE VARIABLES
Identifier $\quad$ Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization . 36241 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Machine 2.Utilization . 34647 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization . 31200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization . 24533 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization . 43867 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization . 48600 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue. NumberInQueue | . 02246 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.NumberInQueue | . 07250 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.NumberInQueue | . 03327 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberInQueue | . 12171 | (Insuf) | . 00000 | 2.0000 | 1.0000 |
| Work Station 2.Queue.NumberInQueue | . 04849 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue. NumberInQueue | . 02542 | (Insuf) | . 00000 | 1.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 19.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3. NumberOut | 20.000 |
| Part 4.NumberOut | 14.000 |
| Part 5. NumberOut | 16.000 |
| Part 6.NumberOut | 12.000 |

## Summary for Replication 11 of 20

tally variables


## Summary for Replication 12 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 45.093 | (Insuf) | 34.000 | 54.176 | 11 |  |
| Part 2.TotalTime | 55.347 | (Insuf) | 44.000 | 66.726 | 19 |  |
| Part 3.TotalTime | 53.394 | (Insuf) | 41.819 | 69.420 | 19 |  |
| Part 4.TotalTime | 51.236 | (Insuf) | 43.000 | 63.858 | 14 |  |
| Part 5.TotalTime | 52.649 | (Insuf) | 39.000 | 64.106 | 21 |  |
| Part 6.TotalTime | 55.998 | (Insuf) | 46.729 | 63.776 | 18 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final | alue |
| Machine 1.Utilization | . 41006 | $6^{--}$(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 33133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 37200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 23999 | 9 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | . 45134 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 48873 | 3 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01801 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 08041 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 02638 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.NumberlnQ | Queue | . 12074 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.NumberlnQ | Queue | . 03427 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06846 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 11.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3.NumberOut | 19.000 |
| Part 4.NumberOut | 14.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 18.000 |

## Summary for Replication 13 of 20

TALLY VARIABLES

| Identifier | Average H | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 45.816 | (Insuf) | 34.000 | 57.480 | 14 |  |
| Part 2.TotalTime | 56.326 | (Insuf) | 40.000 | 76.677 | 24 |  |
| Part 3.TotalTime | 54.848 | (Insuf) | 42.234 | 72.402 | 17 |  |
| Part 4.TotalTime | 52.772 | (Insuf) | 46.000 | 66.438 | 17 |  |
| Part 5.TotalTime | 53.018 | (Insuf) | 43.000 | 72.502 | 16 |  |
| Part 6.TotalTime | 56.647 | (Insuf) | 45.809 | 73.649 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average H | Half Width | Minimum | Maximum | Final |  |
| Machine 1.Utilization | . 38480 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 34340 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | . 32715 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 26467 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 44133 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 49978 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02417 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 09296 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.NumberIn | Queue | . 03393 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 11763 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 02511 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 3.Queue.NumberIn | Queue | . 08304 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 14.000 |  |  |  |  |  |
| Part 2.NumberOut | 24.000 |  |  |  |  |  |
| Part 3.NumberOut | 17.000 |  |  |  |  |  |
| Part 4.NumberOut | 17.000 |  |  |  |  |  |
| Part 5.NumberOut | 16.000 |  |  |  |  |  |
| Part 6.NumberOut | 13.000 |  |  |  |  |  |

## Summary for Replication 14 of 20

| TALLY VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 43.020 | (Insuf) | 35.214 | 50.325 | 10 |  |
| Part 2.TotalTime | 56.413 | (Insuf) | 40.000 | 71.468 | 19 |  |
| Part 3.TotalTime | 55.854 | (Insuf) | 43.021 | 78.827 | 22 |  |
| Part 4.TotalTime | 52.771 | (Insuf) | 43.000 | 66.191 | 17 |  |
| Part 5.TotalTime | 53.366 | (Insuf) | 39.000 | 66.988 | 21 |  |
| Part 6.TotalTime | 52.771 | (Insuf) | 38.159 | 63.565 | 13 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average | Half Width | Minimum | Maximum | Final | alue |
| Machine 1.Utilization | . 37467 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 33000 | 0 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 37261 | 1 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 23200 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 45184 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 51333 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 1.Queue.Numberln | Queue | . 03259 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 03889 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06971 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 4.Queue.NumberlnQ | Queue | . 02176 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 09070 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 12943 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 10.000 |
| :--- | :--- |
| Part 2.NumberOut | 19.000 |
| Part 3.NumberOut | 22.000 |
| Part 4.NumberOut | 17.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 13.000 |

## Summary for Replication 15 of 20

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 44.941 | (Insuf) | 36.000 | 51.215 | 12 |  |
| Part 2.TotalTime | 57.493 | (Insuf) | 42.000 | 74.713 | 27 |  |
| Part 3.TotalTime | 54.500 | (Insuf) | 44.059 | 62.346 | 9 |  |
| Part 4.TotalTime | 51.165 | (Insuf) | 39.000 | 64.912 | 18 |  |
| Part 5.TotalTime | 58.901 | (Insuf) | 42.000 | 75.720 | 15 |  |
| Part 6.TotalTime | 57.448 | (Insuf) | 41.367 | 70.292 | 19 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 39930 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 2.Utilization | . 33772 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 31467 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 4.Utilization | . 25733 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 46263 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 6.Utilization | . 50702 | (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 02292 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 11213 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 03578 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 15658 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 01613 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06775 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 12.000 |  |  |  |  |  |
| Part 2.NumberOut | 27.000 |  |  |  |  |  |
| Part 3.NumberOut | 9.0000 |  |  |  |  |  |
| Part 4.NumberOut | 18.000 |  |  |  |  |  |
| Part 5.NumberOut | 15.000 |  |  |  |  |  |
| Part 6.NumberOut | 19.000 |  |  |  |  |  |

## Summary for Replication 16 of 20

TALLY VARIABLES

| Identifier | Average | Half Width | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 41.992 | (Insuf) | 34.000 | 52.852 | 16 |  |
| Part 2.TotalTime | 55.347 | (Insuf) | 44.557 | 78.018 | 14 |  |
| Part 3.TotalTime | 51.950 | (Insuf) | 41.181 | 76.276 | 15 |  |
| Part 4.TotalTime | 52.089 | (Insuf) | 45.861 | 66.479 | 16 |  |
| Part 5.TotalTime | 53.664 | (Insuf) | 44.000 | 75.000 | 19 |  |
| Part 6.TotalTime | 53.779 | (Insuf) | 40.313 | 67.051 | 20 |  |
| DISCRETE-CHANGE VARIABLES Identifier | Average Half Width |  | Minimum | Maximum | Final Value |  |
| Machine 1.Utilization | . 36038 | ---(Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 31867 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 32117 | 17 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 23800 | (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 42657 | 7 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 47133 | 3 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01166 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 06206 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 1.Queue.NumberIn | Queue | . 04238 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 15366 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 04427 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 06129 | (Insuf) | . 00000 | 2.0000 | . 00000 |

## OUTPUTS

Identifier Value

| Part 1.NumberOut | 16.000 |
| :--- | :--- |
| Part 2.NumberOut | 14.000 |
| Part 3.NumberOut | 15.000 |
| Part 4.NumberOut | 16.000 |
| Part 5.NumberOut | 19.000 |
| Part 6.NumberOut | 20.000 |

## Summary for Replication 17 of 20

TALLY VARIABLES

| Identifier | Average Half Width |  | Minimum | Maximum | Observations |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Part 1.TotalTime | 47.011 | (Insuf) | 34.234 | 63.573 | 9 |  |
| Part 2.TotalTime | 53.503 | (Insuf) | 39.562 | 65.965 | 14 |  |
| Part 3.TotalTime | 50.816 | (Insuf) | 39.000 | 71.377 | 18 |  |
| Part 4.TotalTime | 51.273 | (Insuf) | 39.296 | 61.607 | 22 |  |
| Part 5.TotalTime | 54.766 | (Insuf) | 43.126 | 64.214 | 21 |  |
| Part 6.TotalTime | 53.550 | (Insuf) | 42.561 | 68.697 | 17 |  |
| DISCRETE-CHANGE VARIABLES |  |  |  |  |  |  |
| Identifier | Average H | Half Width | Minimum | Maximum | Final | lue |
| Machine 1.Utilization | . 39917 | $7{ }^{\text {(Insuf) }}$ | . 00000 | 1.0000 | 1.0000 |  |
| Machine 2.Utilization | . 31915 | 15 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 3.Utilization | . 35318 | 8 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 4.Utilization | . 22867 | 7 (Insuf) | . 00000 | 1.0000 | . 00000 |  |
| Machine 5.Utilization | . 43954 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | . 50724 | 4 (Insuf) | . 00000 | 1.0000 | 1.0000 |  |
| Work Station 4.Queue.Numberln | Queue | . 01429 | (Insuf) | . 00000 | 1.0000 | . 00000 |
| Work Station 5.Queue.Numberln | Queue | . 07393 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 1.Queue.Numberln | Queue | . 02814 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 6.Queue.Numberln | Queue | . 11765 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 2.Queue.Numberln | Queue | . 04381 | (Insuf) | . 00000 | 2.0000 | . 00000 |
| Work Station 3.Queue.Numberln | Queue | . 08176 | (Insuf) | . 00000 | 3.0000 | . 00000 |
| OUTPUTS |  |  |  |  |  |  |
| Identifier | Value |  |  |  |  |  |
| Part 1.NumberOut | 9.0000 |  |  |  |  |  |
| Part 2.Numberln | 15.000 |  |  |  |  |  |
| Part 2.NumberOut | 14.000 |  |  |  |  |  |
| Part 3.NumberOut | 18.000 |  |  |  |  |  |
| Part 4.NumberOut | 22.000 |  |  |  |  |  |
| Part 5.NumberOut | 21.000 |  |  |  |  |  |
| Part 6.NumberOut | 17.000 |  |  |  |  |  |

## Summary for Replication 18 of 20

TALLY VARIABLES
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $46.35 \overline{1}$ | (Insuf) | 34.000 | 55.769 | 15 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 55.154 | (Insuf) | 44.000 | 72.506 | 17 |
| Part 3.TotalTime | 51.494 | (Insuf) | 41.000 | 64.768 | 20 |
| Part 4.TotalTime | 51.949 | (Insuf) | 40.292 | 65.791 | 18 |
| Part 5.TotalTime | 58.042 | (Insuf) | 39.000 | 88.603 | 13 |
| Part 6.TotalTime | 52.399 | (Insuf) | 37.970 | 67.863 | 19 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .38267 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .32781 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 3.Utilization | .31445 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .24723 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 5.Utilization | .42778 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 6.Utilization | .50333 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .03439 | (Insuf) | .00000 | 2.0000 | 1.0000 |  |
| Work Station 5.Queue.NumberInQueue | .05171 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 1.Queue.NumberInQueue | .03522 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .15524 | (Insuf) | .00000 | 3.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .03218 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .07265 | (Insuf) | .00000 | 2.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 15.000 |
| :--- | :--- |
| Part 2.NumberOut | 17.000 |
| Part 3.NumberOut | 20.000 |
| Part 4.NumberOut | 18.000 |
| Part 5.NumberOut | 13.000 |
| Part 6.NumberOut | 19.000 |

## Summary for Replication 19 of 20

TALLY VARIABLES


## Summary for Replication 20 of 20

tally variables
Identifier Average Half Width Minimum Maximum Observations

| Part 1.TotalTime | $43.85 \overline{6}$ | (Insuf) | $3 \overline{3} . \overline{349}$ | $54.38 \overline{4}$ | 15 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Part 2.TotalTime | 54.351 | (Insuf) | 45.000 | 60.594 | 15 |
| Part 3.TotalTime | 51.816 | (Insuf) | 43.000 | 72.026 | 13 |
| Part 4.TotalTime | 50.888 | (Insuf) | 39.000 | 77.076 | 22 |
| Part 5.TotalTime | 53.095 | (Insuf) | 44.800 | 68.046 | 21 |
| Part 6.TotalTime | 54.813 | (Insuf) | 43.829 | 74.311 | 14 |

DISCRETE-CHANGE VARIABLES
Identifier Average Half Width Minimum Maximum Final Value

| Machine 1.Utilization | .33594 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Machine 2.Utilization | .33400 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 3.Utilization | .33800 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 4.Utilization | .24867 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Machine 5.Utilization | .44803 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Machine 6.Utilization | .45667 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 4.Queue.NumberInQueue | .02776 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 5.Queue.NumberInQueue | .06092 | (Insuf) | .00000 | 1.0000 | 1.0000 |  |
| Work Station 1.Queue.NumberInQueue | .02392 | (Insuf) | .00000 | 1.0000 | .00000 |  |
| Work Station 6.Queue.NumberInQueue | .10219 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 2.Queue.NumberInQueue | .04409 | (Insuf) | .00000 | 2.0000 | .00000 |  |
| Work Station 3.Queue.NumberInQueue | .07656 | (Insuf) | .00000 | 2.0000 | .00000 |  |

OUTPUTS
Identifier Value

| Part 1.NumberOut | 15.000 |
| :--- | :--- |
| Part 2.NumberOut | 15.000 |
| Part 3.NumberOut | 13.000 |
| Part 4.NumberOut | 22.000 |
| Part 5.NumberOut | 21.000 |
| Part 6.NumberOut | 14.000 |

## APPENDIX D

Example of Summary for Result from Simulation

APPENDIX E<br>Sequence Codification Scheme (SCS)<br>Adopted Form Lawrence (1994)

The first devised SCS represents any given machine by using a pair of numbers: +1 and -1 . Thus, machine A is represented by $(-1,-1)$, machine B by $(-1$, $+1)$, machine C by $(+1,-1)$, and machine D by $(+1,+1)$. Table 4-2 illustrates how a job shop situation is mapped into this SCS. The application of this procedure to all possible job types and machines required a total of 26 digits.

The second scheme takes into account the type of job and the number of operations required by each job type. A ' +1 ' represents an 'active' machine for that operation, while a ' -1 ' indicates that the corresponding machine is 'inactive' or 'not used' for a given operation. For instance, if the first operation for job type 1 is to be performed on machine $A$, it is then represented by ( $+1,-1,-1$ ). This means that machine A is the workcenter used for that operation, while machines B and C are not. If such an operation is instead performed on machine $B$, then, the resulting sequence code would be ( $-1,+1,-1$ ). This SCS requires a total of 43 digits to represent any given sequence (Table 4-3).

A third approach consists of enumerating the whole set of 5184 possible machine sequences. Sequences were alphabetically ordered, i.e. sequence \#1: ABC-ABCD-BCDABD, sequence \#2: ABC-ABCD-BCD-ADB, and so on. After sorting the data, the order number corresponding to each sequence, i.e. a number between 1 and 5184 is converted into its equivalent binary number. In this way, each machine sequence is identified by a unique binary quantity. Finally, all ' 0 's" in the binary code are replaced by ' -1 's'. Here, 13 digits are enough to represent any possible combination of sequences (Table 4-4).

Table 4-2, SCS 1 - Problem mapping

| Job No. | Sequence | Codification (SCS 1) |
| :--- | :--- | :--- |
| 1 | A-C-B | $-1,-1 ; 1,-1 ;-1,1$ |
| 2 | B-C-A-D | $-1,1 ; 1,-1 ;-1,-1 ; 1,1$ |
| 3 | B-C-D | $-1,1 ; 1,-1 ; 1,1$ |
| 4 | D-B-A | 1,$1 ;-1,1 ;-1-1$ |

Table 4-3, SCS 2 - Problem mapping

| Job No. | Sequence | Codification (SCS 1) |
| :--- | :--- | :--- |
| 1 | A-C-B | $1,-1,-1 ;-1,-1,1 ;-1,1,-1$ |
| 2 | B-C-A-D | $-1,1,-1,-1 ;-1,-1,1,-1 ; 1,-1,-1,-1 ;-1,-1,-1,1$ |
| 3 | B-C-D | $-1,1,-1 ;-1,-1,1 ;-1,-1,1$ |
| 4 | D-B-A | $-1,-1,1 ;-1,1,-1 ; 1,-1,-1$ |

Table 4-4, SCS 3 - Problem mapping

| Sequence | Order | Order (binary) | Codification (SCS 1) |
| :--- | :--- | :--- | :--- |
| ABC-ABCD-BCD-ABD | 1 | 0000000000001 | $-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,-1,1$ |
| ABC-BADC-BDC-DAB | 263 | 0001000000111 | $-1,-1,-1,1,-1,-1,-1,-1,-1,-1,1,1,1$ |
| CBA-ACBD-CDB-DBA | 4416 | 1000101000000 | $1,-1,-1,-1,-1,1,-1,-1,-1,-1,-1,-1,-1$ |
| CBA-DCBA-DCB-DBA | 5184 | 1010001000000 | $1,-1,1,-1,-1,-1,1,-1,-1,-1,-1,-1,-1$ |

