AFIT/GSM/LAS/93S-9

BENCHMARK PRODUCTION SCHEDULING PROBLEMS FOR JOB SHOPS WITH INTERACTIVE CONSTRAINTS

THESIS

Stewart W. James
Captain, USAF

Bruno A. Mediate Jr.
Captain, USAF

AFIT/GSM/LAS/93S-9

The views expressed in this thesis are those of the authors and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

AFIT/GSM/LAS/93S-9

BENCHMARK PRODUCTION SCHEDULING PROBLEMS FOR JOB SHOPS WITH INTERACTIVE CONSTRAINTS

THESIS

Presented to the Faculty of the School of Logistics and Acquisition Management

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Systems Management

Stewart W. James, B.S.
Captain, USAF

Bruno A. Mediate Jr., B.S.
Captain, USAF

September 1993

Approved for Public release; distribution unlimited

Acknowledgments

We would like to thank the many AFIT faculty members who have helped us throughout this thesis effort. In particular, we would like to thank our advisors, Major Jacob Simons and Major Wendell Simpson. These two gentlemen invested time in our research above and beyond the call of duty.

In addition, we want to thank the people of the Avraham Y. Goldratt Institute for their support and interest in our research. We would especially like to thank Mr. Robert Newbold who helped us document the *DISASTER™* logic in algorithmic form.

Finally, but most importantly, we would like to thank our families -- Kaye and Sophy James and Vicky and Emily Mediate -- for their patience and understanding. Without their continued support and encouragement this thesis would not have been possible.

Stewart W. James

Bruno A. Mediate Jr.

Table of Contents

Page

Acknowledgments ii

List of Figures vii

List of Tables ix

Abstract x

I. Introduction 1

General Issue 1
Specific Problem 3
Purpose of Research 3
Research Objectives 4
Scope of Research 5
Summary 5

II. Literature Review 7

Introduction 7
Theory of Constraints and Drum-Buffer-Rope 7
The Goal 8
Global Operational Measures 9
Throughput 9
Inventory 9
Operational Expense 10
TOC, DBR, and The Goal 10
The Five Focusing Steps of TOC 10
DBR Scheduling 11
Scheduling Criteria 13
Due Date Assignment 14
Due Date Performance 14
DISASTER™ 15
General Information 15
Software Modules 16
Input Files 16
Output Files 17
Some Unique Concepts/Characteristics 17

Page

Building in Protective Capacity 17
Constraint Types and Identification 18
Time Horizon versus Effective Horizon 19
Combining Job Orders 20
Process versus Transfer Batches 21
DISASTER™'s Scheduling Sequence 21
Subordinate to Market 21
First Day Load Peaks 22
Ruins 22
Backward/Forward Passes 24
Subordinate to Primary Constraint 26
Secondary Constraint Ruins, Backward/Forward Passes . 27
Drum Violation and Drum Loop 27
Subordination 28
DISASTER™ Logic in Algorithmic Form 28
DISASTER™ Limitations 29
Summary 30

III. Research Methodology 31

Research Design 31
Experimental Design 31
Split-Plot Factorial Design 32
Production Variables 34
Experimental Factor 1 34
Experimental Factor 2 36
Experimental Factor 3 37
Background Variables and Benchmark Problem Development . 39
Data Collection of Dependent Variables 49
Type of Analysis for Experimental Results 51
ANOVA Model 52
Hypotheses Tested in ANOVA 53
Assumptions of ANOVA 54
Statistical Procedure to Test Hypotheses 55
Tukey's Procedure 56
ANOVA in this Experiment 56
Summary 57

IV. Findings 59

Overview 59

Page

How the Experiment Was Accomplished 59
Identifying Interactive Constraints 60
Analysis of Due Date Performance 63
Assumptions of ANOVA Addressed 63
Total Days Late 63
Tukey's Results for %RCF 65
Tukey's Results for %ΔRCF 65
Maximum Tardiness 66
Tukey's Results for %RCF 67
Tukey's Results for %ΔRCF 68
Analysis of the Difference Between
the Best and Worst Schedules 72
Descriptive Statistics for the Difference Between
Best and Worst Schedules 73
Assumptions of ANOVA Addressed 73
%DIFFTDL 74
Tukey's Results for %ΔRCF 74
%DIFFMTD 76
Decision Rules for Selecting the Primary Constraint 77
Nuances Involved With Using *DISASTER™* 80
First Nuance 80
Second Nuance 82
Third Nuance 85
Summary 86

V. Conclusions 87

Significance of this Research 87
Future Research 91

VI. Glossary 94

Appendix A: *DISASTER™* Logic in Algorithmic Form 97

Appendix B: Due Date Assignment Data 107

Appendix C: Network Representation of Benchmark Problems 113

Appendix D: Summary Data of *DISASTER™* Output 142

Page

Appendix E:	Assumptions of ANOVA Model for TDL_{best} and MTD_{best} . . .	150
Appendix F:	ANOVA Results for TDL_{best}	153
Appendix G:	ANOVA Results for MTD_{best}	160
Appendix H:	Assumptions of ANOVA Model for %DIFFTDL and %DIFFMTD	166
Appendix I:	ANOVA Results for %DIFFTDL	169
Appendix J:	ANOVA Results for %DIFFMTD	173
Bibliography	. . . .	176
Vita	. . . .	179

List of Figures

Figure		Page
1.	Simple Production Operation	20
2.	Ruins for Primary Constraint	23
3.	Ruins for Primary Constraint With Interaction	25
4.	Schedule for Batches After Backward Pass	25
5.	Drum Schedule for Batches After Forward Pass	26
6.	Methodology Flowchart	58
7.	Drum with Small %ΔRCF	62
8.	Drum with Large %ΔRCF	62
9.	Mean TDL_{best} versus %RCF	65
10.	Mean TDL_{best} versus %ΔRCF	66
11.	Mean MTD_{best} versus %RCF	68
12.	Mean MTD_{best} versus %ΔRCF	69
13.	Mean TDL_{best} versus Plant Type	70
14.	Mean MTD_{best} versus Plant Type	70
15.	A Comparison of Total Processing Time per Process Batch for Each Plant Type	72
16.	%DIFFTDL versus %RCF	76
17.	Revised Completion Date Heuristic Example 1	83
18.	Revised Completion Date Heuristic Example 2	84
19.	Revised Completion Date Heuristic Example 3	84

Page

20. Transfer Batch Example 86

21. Variation in Rod Length With Constant Total Processing Time for Process Batches 92

List of Tables

Table ... Page

1. Levels of Factor 1, %RCF Lower Constraint Resource 35
2. Levels of Factor 2, %ΔRCF Between Constraint Resources 36
3. Levels of Factor 3, Plant Type 39
4. Background Variables 41
5. Product Type Constraint Interaction 47
6. ANOVA Model Variables for this Experiment 57
7. ANOVA Table for TDL_{best} 64
8. ANOVA Table for MTD_{best} 67
9. Descriptive Statistics for the Best and Worst Schedules for TDL and MTD 74
10. ANOVA Table for %DIFFTDL 75
11. ANOVA Table for %DIFFMTD 77
12. Performance of Decision Rules in This Experiment 78

AFIT/GSM/LAS/93S-9

Abstract

United States Air Force (USAF) depots have expressed interest in utilizing *DISASTER™* production scheduling software to schedule their maintenance operations. *DISASTER™* attempts to increase system throughput by building effective schedules for system constraint resources. However, when a system contains multiple, interactive constraints, *DISASTER™* builds the constraint schedules one at a time. Since each successive schedule must adhere to timing restrictions imposed by previous constraint schedules, the quality of the schedules produced by *DISASTER™* is dependent upon the sequence in which the constraints are scheduled. This thesis first developed a set of benchmark problems which provided a diversity of scheduling scenarios. These benchmark problems were then used to determine the relationship between the constraint scheduling sequence and the quality of the schedules *DISASTER™* produced. The researchers found that the sequence in which the constraints were scheduled has an effect on the due date performance of the schedules. This knowledge has the potential to produce substantial improvements in the quality of USAF depots' schedules. In addition, the problems developed serve as a benchmark for future research which compares alternative scheduling algorithms to *DISASTER™*.

BENCHMARK PRODUCTION SCHEDULING PROBLEMS FOR JOB SHOPS WITH INTERACTIVE CONSTRAINTS

I. Introduction

General Issue

Scheduling production in a job shop manufacturing environment is extremely challenging (McKay et al, 1988:85). A job shop is a factory which produces made-to-order product types where each product type may require a unique combination of resources and processing times (Heizer et al, 1993:229). Many United States Air Force (USAF) depot maintenance facilities are job shops. These maintenance facilities involve many types of activities "ranging from the refurbishment and modification of complete aircraft to the repair and calibration of electronic components" (Demmy and Petrini, 1992:11).

One objective in scheduling the resources of a job shop is meeting job order due date requirements (Baker, 1984:1093). Due date performance is important in today's manufacturing world for a company to be competitive (Horngren and Foster, 1991:916). Since USAF depot maintenance facilities operate on a fee-for-service basis, they "must provide their customers quality products, in a timely fashion, at the lowest possible cost...much like a business in the private sector" (Demmy and Petrini, 1992:7). A job shop promises to deliver a specified quantity of a product type by a certain date. If the job shop fulfills its promise a greater percentage of the time than the job shop's competitor, it will maintain a competitive edge (Goldratt and Fox, 1986:36). Due date performance can be measured in different ways, including proportion of late job orders, mean tardiness among all job orders, and average tardiness of the late job orders (Baker, 1984:1093).

In recent years the Drum-Buffer-Rope (DBR) scheduling technique has been introduced for job shop scheduling. DBR scheduling was developed under the Theory of Constraints (TOC) philosophy by Eliyahu Goldratt in his books *The Goal*, *The Race*, and *The Haystack Syndrome*. (Some of the terminology used by this theory and included in this thesis may be unfamiliar to the reader. The researchers have provided a glossary of key terms in Chapter VI.) Ogden Air Logistic Center (ALC) has applied the TOC concepts to manage aircraft wheel repair and has had successful results. The TOC concepts resulted in a decrease in flowtime by 75%, while increasing throughput by 38%. This USAF success story is not unique; the other four ALCs have had similar successes after implementing the TOC principles (Demmy and Petrini, 1992:6).

Both TOC and DBR scheduling are based on the fundamental principles that the best way to schedule a manufacturing system is to exploit the system's constraint(s) and subordinate the other resources to the constraint(s) (Goldratt and Fox, 1986:98). Any production resource that has more demand placed on it than it has capacity is defined as a bottleneck. When a bottleneck has the effect of restricting the ability of a system to achieve its goal, it is called a constraint (Simons and Moore, 1992:2). A job shop can have multiple resources which are constraints. The Avraham Y. Goldratt Institute has found that some manufacturing environments do have multiple constraints (Rose, 1993). If one constraint process station feeds another constraint process station somewhere in the production operation, the constraints are said to be interactive (Newbold Atch, 1990:1). The existence of interactive constraints complicates scheduling even further when trying to meet a due date performance objective.

DISASTER™ is a production scheduling software package based on the DBR scheduling technique (*DISASTER™* pamphlet, 1991:1). The software is a product of the Avraham Y. Goldratt Institute. The Institute's founder is Eliyahu Goldratt who, as previously stated, developed both the Theory of Constraints and the DBR scheduling technique. Since the USAF ALCs had such great success applying TOC principles, the USAF ALCs are now interested in using *DISASTER™*. Currently, Warner-Robins ALC's Tooling and Computer Numerical Control Branch is in the process of implementing *DISASTER™* for the scheduling of its operations.

Specific Problem

In the event of interactive constraints, DBR, as implemented in *DISASTER™*, schedules the constraints sequentially in light of any schedules already developed for other constraints (Newbold, 1992; Newbold Atch, 1990:1). The scheduler must specify which constraint is to be scheduled first. The quality of the final schedule in terms of due date performance may be affected by the sequence in which the constraints are scheduled. The sequence chosen "could have significant implications for both the short-term bottom line and the long-term strategy of the company" (Newbold, 1992). However, the relationship between the constraint sequence and the quality of the schedule has not been established. In other words, while it has been established that constraint sequence affects schedule quality, the specific nature of that relationship has not yet been characterized. Knowledge of this relationship has the potential to produce substantial improvements in the quality of USAF depot schedules.

Purpose of Research

The purpose of this research effort is twofold. The first purpose is to determine the relationship between the quality of *DISASTER™*'s schedules and the constraint sequence chosen for a diversity of scheduling scenarios. However, there are currently no benchmark problems available to evaluate the impact constraint sequence has on the due date performance of the schedules produced by *DISASTER™*. Therefore, the second purpose is to develop a set of benchmark scheduling problems for job shops with interactive constraints.

In addition, the quality of *DISASTER™*'s algorithm is unknown. As stated earlier, no benchmark problems exist to evaluate the quality of this algorithm. Therefore, these benchmark problems can also be used to compare *DISASTER™*'s due date performance to alternative methods for scheduling interactive constraints. The thesis team of Captain Barak Carlson and Captain Christopher Lettiere concurrently developed an alternative DBR scheduling algorithm which simultaneously schedules all of the production system's constraints (see AFIT Thesis AFIT/GSM/LAS/93S-3). Both theses concentrate on the effect of constraint exploitation on throughput of the production operation as measured by due date performance. The benchmark problems developed in this study were used to test the Carlson-Lettiere algorithm. In their thesis, Captain Carlson and Captain Lettiere also analyzed and compared their algorithm's output schedules with the *DISASTER™* solutions produced from this study.

Research Objectives

This study has five objectives:

1) to define the *DISASTER™* scheduling logic in algorithmic form

2) to develop a set of benchmark problems that represent a diversity of scheduling scenarios with respect to the capabilities of the *DISASTER™* algorithm

3) to produce solutions (schedules) for the benchmark problems using the *DISASTER™* software

4) to evaluate *DISASTER™*'s due date performance as the levels of the factors change to ensure the benchmark problems produce a diversity of scheduling scenarios

5) to determine the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences.

Scope of Research

This research effort will focus only on the job shop with two resource constraints. The Avraham Y. Goldratt Institute has found that in most manufacturing environments there are only two or three constraints (Rose, 1993).

DISASTER™ Version 1 is the software package of choice for two reasons. First, it was developed by the Avraham Y. Goldratt Institute. Second, *DISASTER™* is the only scheduling package available to the researchers which schedules using the DBR technique.

Schedules produced by *DISASTER™* will be evaluated solely on their due date performance. A cost comparison of the schedules is not available since the benchmark problems strictly address schedule performance rather than schedule cost. In addition, this study does not address a schedule's impact on the level of work-in-process inventory in the production operation.

Summary

This chapter provided a brief overview of this thesis research effort. Chapter II provides additional background on the research topic through a review of relevant literature. Following the literature review, Chapter III identifies the methodology used to design and conduct the research effort. Chapter IV contains the findings and analysis of the schedules produced by *DISASTER™* for the developed benchmark problems. In addition, Chapter IV concludes with a discussion of the significance of the findings and some of the nuances involved with using *DISASTER™* which were discovered by the researchers. Chapter V contains a summary of this thesis as well as recommendations for future research efforts. Finally, Chapter VI is a glossary of important terms which are used throughout this thesis.

II. Literature Review

Introduction

Recently, Eliyahu Goldratt has proposed TOC as an alternative for managing a job shop operation. Goldratt's scheduling software package, *DISASTER™*, produces schedules based on the principles of TOC (*DISASTER™* pamphlet, 1991:1).

This chapter first reviews the TOC philosophy and its Drum-Buffer-Rope (DBR) scheduling technique. Second, the importance of due date performance in today's manufacturing environment is discussed. Third, due date assignment rules are reviewed. Finally, *DISASTER™*-specific terminology is defined and the logic *DISASTER™* uses to build schedules is presented.

A job shop is a factory that produces made-to-order products, as opposed to a repetitive assembly line type environment (Heizer et al, 1993:229). Each job order may require different raw materials, processing order, and processing times (Heizer et al, 1993:229). A job shop is an extremely challenging scheduling environment since there are so many variables (McKay et al, 1988:85). Because of the extreme complexity, much research has been done on the scheduling of the job shop (McKay et al, 1988:84). TOC along with its scheduling technique, DBR, is one of the most recent of many techniques which have been introduced to schedule and manage the job shop manufacturing environment.

Theory of Constraints and Drum-Buffer-Rope

TOC, as proposed by Eliyahu Goldratt in his books *The Goal* and *The Race*, has been introduced into the production scheduling world within the last few years (Simons and Moore, 1992:2). TOC is based on the belief that the entire manufacturing plant should be managed by controlling its constraints (Fox, 1984:56-57). A constraint is any resource that limits a system's throughput (Fox, 1984:56). Goldratt has distinguished between two types of constraints in his book *The Haystack Syndrome*. A bottleneck resource is a resource "that does not have sufficient available capacity to strictly satisfy the demand" (Goldratt, 1990:189). By contrast, a capacity constraint resource is a non-bottleneck resource that lacks the protective capacity sufficient to protect against the negative impacts of variability in the production operation (Goldratt, 1990:188). Protective capacity is "the percentage of capacity for any non-constraint resource that remains unscheduled so that it will be able to catch up after a breakdown or other mishap" (*DISASTER™* Manual - Jump Start, 1990:61). The difference between bottlenecks and capacity constraint resources is that a bottleneck does not have enough available capacity to satisfy the demand, while a capacity constraint resource does not have enough protective capacity to account for fluctuations in the production operation. In either case, the resource is treated as a constraint if it restricts the operation's throughput.

A job shop may have multiple constraints, but in most cases a job shop will have no more than two or three (Rose, 1993). Often the constraints in a job shop will be interactive. "An interactive constraint is defined as a constraint resource which is fed by, or which feeds, another already-defined constraint resource" (Newbold Atch, 1990:1). This research effort will concentrate on job shops with two interactive constraints. In addition, this effort will focus only on bottleneck resources, that is resources that have more demand placed on them than available capacity.

The Goal. The ultimate goal of any manufacturing organization is to make money (Goldratt and Cox 1992:65). The three measurements that define how a company is doing in relation to this goal are return on investment, net profit, and cash flow. These measurements will be referred to as the bottom line measurements (Goldratt and Fox, 1986:30). Return on investment is how much money is made in relation to how much money is invested. Net profit is the amount of money made after expenses. Cash flow is the amount of money coming in per accounting period (Goldratt and Fox, 1986:20). An organization must take steps to increase these three measurements simultaneously in order to make more money (Goldratt and Fox, 1986:30).

Goldratt has stated that cost accounting is the number one enemy of productivity (Goldratt and Cox, 1992). Why does he believe this? Cost accounting emphasizes the local efficiencies of individual processing units, as opposed to increasing the effectiveness of the entire plant (Goldratt and Cox, 1992:27-28). This incorrect emphasis can lead managers to make improper decisions. For example, traditional analysis based on cost accounting may lead to extra people or an additional machine being placed at a process station that will not increase the throughput of the plant, but will only increase the efficiency of that particular process station. The goal of the company has not been addressed. Goldratt has another alternative: use global operational measures (Goldratt and Fox, 1986:28).

Global Operational Measures. As opposed to measuring each individual process station against cost accounting measures, TOC emphasizes measuring the entire plant against three global operational measures. These operational measures are throughput, inventory, and operational expense (Jayson, 1987:21).

Throughput. Throughput is defined as "the rate at which a system generates money through sales" (Goldratt and Fox, 1986:59). In other words, producing goods is not throughput; the goods have to be sold.

Inventory. Inventory is "all the money that the system has invested in purchasing things it intends to sell" (Goldratt and Fox, 1986:59). Goldratt's definition of inventory deviates from the normal definition. His definition does not include the value added to the inventory by direct labor and overhead because the added value may cause improper decisions due to cost accounting principles. Defining inventory in his proposed way eliminates potentially deceptive inventory profits and losses. Profits can only be generated by throughput, not by producing large amounts of inventory (Goldratt and Fox, 1986:28).

Operational Expense. Operational expense is "all the money the system spends in order to turn inventory into throughput" (Goldratt and Fox, 1986:60). This definition includes everything from employees' wages to depreciation of capital expenditures. This is a global measurement because labor and overhead are not allocated to product types using some arbitrary procedure; they are kept at the factory level.

TOC, DBR, and The Goal. Since all three global operational measures affect all three of the bottom line measurements, a system is needed which simultaneously increases throughput, decreases inventory, and decreases operational expense (Goldratt and Fox, 1986:66). TOC and its scheduling technique, DBR, serve to facilitate such improvements.

The Five Focusing Steps of TOC. TOC is based on the principle that the best way to control your system is to concentrate on the constraint (Fox, 1984:56-57). As mentioned earlier, a constraint is any resource that limits throughput. Such limitations result from an insufficiency of either available capacity or protective capacity, thereby distinguishing the constraint as a bottleneck or capacity constraint resource, respectively. Any resource that is not a constraint "does not have demand for 100% or more of its capacity" (Simons and Moore, 1992:2). Since the constraint determines the amount of throughput, any time lost on the constraint is lost for the entire system (Fox, 1984:58). Therefore, the best way to improve the system is to better manage the constraint. TOC offers a five step method for managing a system's constraint (Goldratt and Cox, 1992:303).

1. <u>Identify the system's constraint.</u> The system may have one or more resources with more demand placed on it than it has capacity (available or protective). A

constraint could be many things, from the processing time available on one machine to packaging material required for shipping.

2. Exploit the system's constraint. Everything possible must be done to ensure maximum use of the constraint. An example of this is operating the constraint during lunch hour.

3. Subordinate everything else to the constraint. All process stations which feed the constraint must produce exactly what the constraint needs and nothing more. For example, if a non-constraint can produce eight parts per hour and the constraint can only produce four parts per hour, then the non-constraint should only produce at the rate of the constraint. Any further production will only lead to an increase in work-in-process (WIP) inventory.

4. Elevate the system's constraint. Elevating the system's constraint means increasing the capacity of the constraint. An example of this is buying another machine that is capable of the same processes as the constraint. As mentioned earlier, any increase in the capability of the constraint will increase the capability of the entire system.

5. If in the previous steps a constraint has been broken, go back to step one, but do not allow inertia to cause a system's constraint. Once the original constraint is no longer the system's constraint, start to look for another.

DBR Scheduling. DBR scheduling puts the principles of steps one through three of the five focusing steps into action. Since the constraint controls the throughput of the entire system, the constraint must set the pace for the rest of the system. The constraint is the 'drum' that lays the beat the rest of the system must march to (Goldratt and Fox, 1986:98). If any of the non-constraints produce more than the constraint can handle, throughput will not increase but inventory will. Thus, the rest of the system must march to the beat of the constraint.

Any raw material released into the system at a faster rate than the beat of the drum will not result in increased throughput, only increased inventory. Since one of the objectives of TOC is to decrease the level of inventory, any material released ahead of the drum beat is counterproductive. Therefore, a rope must be tied from the constraint(s) to the raw material in order to control the rate of release of the raw material to coincide with the rate at which the constraint processes parts (Goldratt and Fox, 1986:98).

A schedule must take variability into consideration, or the schedule will not be robust enough to be upheld in practice. DBR protects the constraint of the system from variability of upstream process stations by placing inventory 'buffers' in a few strategic places around the system (Goldratt and Fox, 1986:98-104). Since the constraint controls the throughput of the system, only the constraint process stations of the operation need to be buffered against variability. The buffers should only contain enough material to keep the constraint busy for a predetermined amount of time. Once the buffer is full, the upstream process stations should stop producing (Goldratt and Fox, 1986:98). Should the upstream process stations continue to produce once the buffers are full, throughput will not increase but WIP inventory will.

This research effort focuses on the exploitation of the 'drum.' In particular, it addresses the due date performance of DBR schedules for job shop environments with two interactive constraints. Previous research has been accomplished on DBR scheduling (Ramsay et al, 1990; Schragenheim and Ronen, 1990; Fawcett and Pearson, 1991; Gargeya, 1992). Ramsay and others, as well as Schragenheim and Ronen, performed simulation analysis of a single job shop environment with only one resource constraint or the potential for a resource constraint. Fawcett and Pearson's study focuses on management of constraint resources in different manufacturing environments. Their study is purely qualitative in nature, and does not attempt to quantify any differences between the manufacturing environments. Gargeya's research effort quantitatively evaluates resource constraint measures for a job shop with two constraints. The purpose of Gargeya's effort is to determine a resource constraint measure for input into a shop loading algorithm.

This thesis expands upon these efforts. As opposed to Ramsay and others and Schragenheim and Ronen, this thesis analyzes multiple job shop environments (rather than a single environment) with two resource constraints (rather than one resource constraint). Whereas Fawcett and Pearson's study qualitatively discussed manufacturing environments with constraints, this research quantifies the manufacturing environments for use in an experiment. Finally, one of Gargeya's resource constraint measures is used in developing the benchmark problems developed in this thesis. This thesis analyzes *DISASTER™*'s due date performance for multiple job shop environments with two bottleneck resources at various levels of resource constraint measures.

Scheduling Criteria

Traditionally, researchers of production scheduling problems concern themselves with two criteria: cost and performance (Graves, 1981:648). Schedule cost refers to measures such as setup costs, holding costs, and stockout costs (Graves, 1981:648). Schedules which provide fewer setups, less inventory, and fewer stockouts are preferable. This research effort does not focus on the cost of a schedule, but rather on its performance.

Schedule performance can be measured in many ways, including percentage of tardy job orders, total days late for a set of job orders, average tardiness for a set of job orders, maximum tardiness, or makespan -- which is the time from the beginning of the first job order until the completion of the last job order (Graves, 1981:649). The performance measurement for a schedule is determined by the specific management objective of the manufacturing plant. It is impossible to simultaneously optimize all performance measures, thus management must decide upon a desirable objective and schedule operations accordingly (Woolsey, 1982:115; Baker, 1984:1093). For example, assume two manufacturers' schedules have ten total days late for all scheduled job orders due to lack of available capacity. An example of differing management objectives may be seen when one manufacturer opts to make ten customers wait one day for their job orders while another manufacturer prefers to make one customer wait ten days. The first manufacturer minimized the maximum tardiness, and the second manufacturer minimized the number of tardy job orders.

Due Date Assignment. While this area is not the focus of this study, a brief discussion on how due dates are assigned is relevant for the development of the benchmark problems. Other researchers have studied due date assignment procedures (Baker and Bertrand, 1981; Baker, 1984; Ragatz and Mabert, 1984; Dumond and Mabert, 1988). The fundamental approach for internally assigning due dates is the same. When the manufacturer, as opposed to the customer, determines the due date, the due date is said to be internally assigned. First, the job order's arrival day (the day a job order can begin production) is determined; then the total flowtime of that job order is estimated and added to the job order's arrival day to estimate the job order's due date. Flowtime may be estimated by multiplying a constant by either the total processing time required or total number of process stations required for that job order's product type (Ragatz and Mabert, 1984:29). When using the total number of process stations to estimate flowtime, due dates may be determined using the following formulae:

$$\text{Flow Time} = (\#\ \text{process stations}) \cdot (\text{constant})$$
$$\text{Due Date} = \text{Arrival Date} + \text{Flow Time}$$

Due Date Performance. Due date performance is important to today's manufacturing plants: "Industry surveys report that superior on-time performance can provide a company with a competitive advantage" (Horngren and Foster, 1991:916). Goldratt and Fox agree that responsiveness to the customer, in terms of shorter quoted lead times and due date performance, is one way to gain a competitive advantage (Goldratt and Fox, 1986:36).

The scheduling objective that management chooses depends on the product type(s), demand, competition, and the specific manufacturing environment. For a job shop, job order completion date should be an important management objective: "In a job shop, the emphasis is on 'when can I promise to deliver this specific client's order?'" (Turner, 1991:62). Establishing a job order's due date is only the first step in due date performance.

After job order due dates have been established, the goal of the job shop is to meet all the promised due dates. If there is a constraint (or multiple constraints) in the operation, the manufacturer will be unable to complete every job order by its required due date. The job shop is loaded beyond its available capacity during the time frame in which those job orders become due. This study addresses the scheduling of production operations with a given set of job orders and due dates in order to best meet a due date performance management objective.

DISASTER™

General Information. For a complete analysis of the *DISASTER™* software interface, options, and instructions the researchers suggest reviewing the software's manuals supplemented by reading AFIT Thesis AFIT/GLM/LSM/91S-56 by Captain Jefferson L. Severs. For this research effort, the review of *DISASTER™* focuses on the software's production scheduling logic. According to Coral Rose of the Avraham Y. Goldratt Institute, success stories concerning the implementation of *DISASTER™* have been limited by lack of user understanding and implementation of the concepts behind the software (Rose, 1993). Therefore, a thorough understanding of the principles behind *DISASTER™* is crucial for successful implementation. Unless otherwise noted, the information provided in this section is the researchers' compilation of the concepts and ideas found in *The Race*, *The Haystack Syndrome*, the *DISASTER™* software documentation, and correspondence and notes from Robert Newbold of the Avraham Y. Goldratt Institute.

Software Modules. The *DISASTER™* scheduling package contains three software modules: NETGEN, CALENDAR, and SCHEDULE. The NETGEN and CALENDAR modules are used to create data files used in the SCHEDULE module. Data about the specific manufacturing environment are input in these two modules to build the files required by SCHEDULE. SCHEDULE then attempts to maximize the throughput of the plant through "an iterative process of identifying a resource constraint, exploiting it to its fullest and subordinating all other resources to supply the material needs to the constraints thus far identified" (*DISASTER™* pamphlet, 1991:1).

Input Files. *DISASTER™* schedules are based on the **specific** manufacturing environment for which the schedule is being developed. Thus, data describing the manufacturing environment and production operation must be collected. For clarity, the terms resource, process station, and operation must be defined. Resource refers to the type of machine or type of labor. Process station refers to a particular resource, setup in a particular manner, to perform work in a particular place in the production sequence of a product type. Operation refers to all process stations required to produce all product types.

DISASTER™ requires five ASCII files for input into the NETGEN module:

1) ARROW FILE (*.ARR) The arrow file describes how the WIP inventory flows through the process stations for the plant's product types.

2) RAW MATERIAL FILE (*.RAW) The raw material file identifies the raw materials required to produce the product types.

3) STATION FILE (*.STN) The station file describes the resource type, the processing time per unit, and setup time required for each process station.

4) RESOURCE FILE (*.RES) The resource file describes the type and quantity of each resource available.

5) ORDER FILE (*.ORD) The order file contains the list of job orders, their product type, the quantity, and the due date for each job order.

NETGEN creates a binary Tasks Structures Net file (*.NET) from these five files. Another binary file (*.LIB) is developed by the CALENDAR module to describe the work hours of the production plant. This module uses a menu-driven user interface and does not require importing ASCII files.

Output Files. The binary files created by NETGEN and CALENDAR are used by the SCHEDULE module to develop the production schedule. *DISASTER™* produces eleven output files for each schedule developed. Nine of these eleven files contain data not of interest for this thesis effort. These include such files as the overtime schedule file, the screen dump file, and the program activity log file. The remaining two files include data concerning the schedule(s) for the constraint(s) as well as the overall schedule performance. These two output files are:

1) CONSTRAINTS SCHEDULE FILE (*.SD1) The .SD1 file contains the schedules for each constraint resource by process station.

2) NEW ORDER DUE DATES FILE (*.SD3) The .SD3 file contains the original due date and the estimated completion date for each job order contained in the schedule.

Some Unique Concepts/Characteristics.

Building in Protective Capacity. One advantage of *DISASTER™* is that it "acknowledges the existence of Murphy [as in Murphy's Law] and statistical fluctuations"

(*DISASTER™* pamphlet, 1991:1). This acknowledgment of reality makes the computed schedule relatively immune to problems that arise throughout the production cycle (*DISASTER™* pamphlet, 1991:1). *DISASTER™* does this by strategically placing buffers of work-in-process (WIP) inventory in the production cycle. The size of the buffers are determined by the variability of the upstream process stations. These buffers are expressed in terms of time, where the amount of WIP held in the buffer is calculated based upon the processing time of the next sequential process station. There are three types of time buffers: resource constraint buffers, assembly buffers, and shipping buffers (Demmy and Petrini, 1992:8). A resource constraint buffer is a stock of WIP before a resource constraint process station which protects the throughput of the constraint by assuring it is never idle due to disruptions upstream in the production cycle. An assembly buffer is a stock of WIP produced by non-constraint resources placed before an assembly process station which is also fed by parts which have been processed by a constraint(s). This buffer assures the parts produced by the constraint(s) are not delayed due to a shortage of parts produced by non-constraint resources. A shipping buffer is a stock of finished goods of a product type which protects the integrity of promised due dates for the job order. This buffer protects these due dates from disruptions at constraint process stations or at non-constraint process stations downstream from the final constraint process station for that product type.

Constraint Types and Identification. Recall the difference between bottlenecks and capacity constraint resources: a bottleneck does not have enough available capacity to satisfy the demand and a capacity constraint resource does not have enough protective capacity to account for fluctuations in the production operation. This implies that non-bottleneck resources can be capacity constraint resources.

In addition to this, it may be possible for bottlenecks to not be identified as capacity constraint resources since *DISASTER™* sequentially schedules constraints. This situation occurs when there are multiple bottlenecks in the production operation. The first bottleneck resource is identified and scheduled. The initial schedule is unable to meet the required demand because more load is placed on the resource than it has available capacity. Consequently, the schedule ultimately produced may project job order completion times later than job order due dates. The result is that demand is reduced for the other resources. Since these revised completion times generate a lower level of demand, the other bottlenecks may now have enough protective capacity to meet these revised completion dates.

Constraints are also characterized by the production operation. Figure 1 identifies a simple production operation with three resource types and three process stations. A primary constraint is a constraint which does not interact with another constraint when it is identified. For example, in the process of scheduling the production operation in Figure 1, if only Resource C is identified as a constraint by *DISASTER™*, Resource C is a primary constraint. An interactive constraint is a constraint that has at least one of its process stations which feeds, or is fed by, another constraint process station. In this example, if after Resource C has been identified as a primary constraint and scheduled, Resource A is also identified as a constraint, Resource C and Resource A are interactive constraints. A secondary constraint is a constraint which interacts with another previously identified and scheduled constraint. In this example, Resource A is a secondary constraint.

Time Horizon versus Effective Horizon. *DISASTER™*'s SCHEDULE module opens with a window that asks for various schedule parameters including buffer sizes, overtime limits, and percent protective capacity. In addition, *DISASTER™* requests a start and end date for the time horizon. The time horizon is the length of time to use in scheduling the resources. In other words, the schedule *DISASTER™* produces spans the length of time identified by the time horizon.

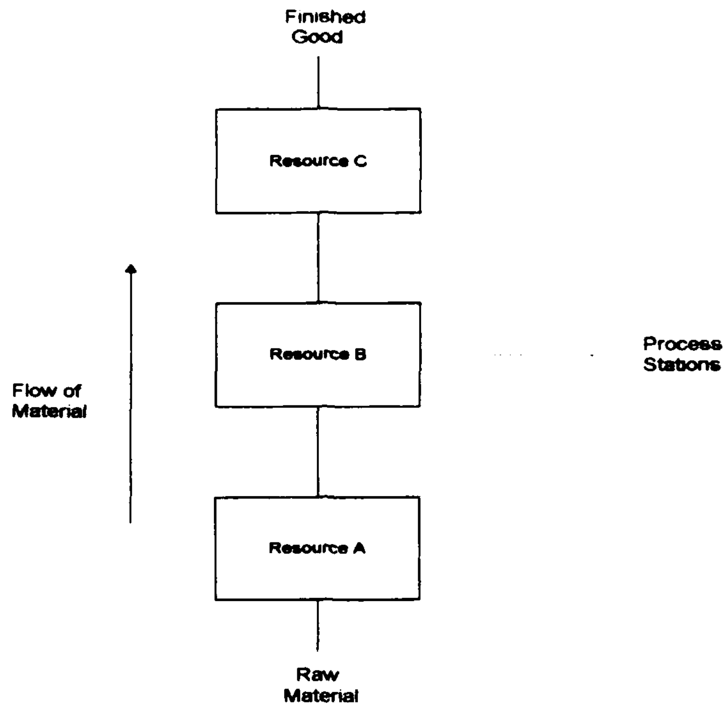


Figure 1: Simple Production Operation

From the time horizon information, another horizon (known as the effective horizon) is calculated. The effective horizon is an expanded horizon used to account for job orders that may have due dates just after the end of the time horizon. These job orders may require processing inside the time horizon, and therefore their load requirements should be included in the calculated schedule. In order to determine the length of the effective horizon, the size of the shipping buffer is added to the end of the time horizon.

Combining Job Orders. As previously mentioned, the order input file (*.ORD) includes information about each job order. However, *DISASTER™* requires that separate job orders for the same product type and with the same due date be combined into one job order. *DISASTER™* requires combining these job orders to save setup times that may otherwise be necessary if these job orders remained two separate job orders. *DISASTER™* then does not recognize these as different job orders during the development of a schedule. The impact of this requirement is that these job orders are combined throughout the scheduling process. Therefore, the job orders will both have the same revised completion date. This merging of the job orders decreases *DISASTER™*'s flexibility to schedule these two job orders: either both job orders are on time or both job orders are late.

Process versus Transfer Batches. A process batch is a batch of parts which is processed by a resource before a setup is performed for the resource to run another process batch for a different process station (Fox, 1984:59). A transfer batch is a batch of parts which must be produced before being physically moved from one resource process station to another (Fox, 1984:59). *DISASTER™* allows for consecutive process stations to overlap process batches. This necessitates the use of transfer batch sizes less than the size of the process batches.

For example, assume process stations A and B perform consecutive processes in a production operation. Process station A has a process batch size of 100 units, and each unit takes 1 minute of processing time. The start time for process station A is the start of the day and the finish time for process station A is 100 minutes later. Meanwhile, process station B is scheduled to begin 40 minutes after the start of the day. If process station B waited for process station A to complete its entire process batch, process station B would be 60 minutes behind schedule. Instead, a transfer batch of no more than 40 units must be shifted from process station A to process station B to ensure process station B can begin by the 40 minute point.

DISASTER™'s Scheduling Sequence. The following sequence of topics provides the general flow of *DISASTER™*'s scheduling of a job shop with two interactive constraints.

Subordinate to Market. At this point, all resources are currently non-constraints since none have yet been identified as constraints. The best place for *DISASTER™* to begin is by subordinating to the market (job order due dates), because due dates represent the only **known** constraint at the start of scheduling. (Note that the limit of current demand is usually considered to be a market constraint.) Subordination "performs backward scheduling on all the non-constraint resources" (*DISASTER™ Manual - Jump Start*, 1990:95). Backward scheduling is a process which moves backwards one day at a time along a time axis, for each resource, from the latest date of the effective horizon. During this movement *DISASTER™* sums all loading required per day for each resource. When a resource's capacity limit is reached for a given day, *DISASTER™* moves backward to the next earlier day.

First Day Load Peaks. Since subordination moves backward in time, overloads on the non-constraint resources are pushed to earlier days. However, it is not possible to push these overloads earlier than the start date of the time horizon. If resources have more load scheduled for the first day than they have capacity, *DISASTER™* identifies these as First Day Load Peaks on those resources. It is from this list of resources that the first resource constraint can be identified.

Ruins. Once a resource has been identified as the primary constraint, *DISASTER™* displays what it calls the 'ruins' for all process batches required by that resource. The ruins display all process batches to be processed on the constraint for all job orders with no regard to the finite capacity of the constraint. For example, consider a set of job orders requiring only one process station on the primary constraint (with no constraint process station feeding another constraint process station). Figure 2 identifies the ruins for a primary constraint. Each 'brick' represents the total processing time for a batch. The ruins are constructed by calculating the finish time for each process batch. The finish time is calculated as the job order's due date minus one shipping buffer. The start time for each process batch is calculated as the finish time minus the total processing time required for the process batch. Figure 2 identifies that two units of the primary constraint resource are required. If only one unit is available, the schedule for the process batches is not feasible.

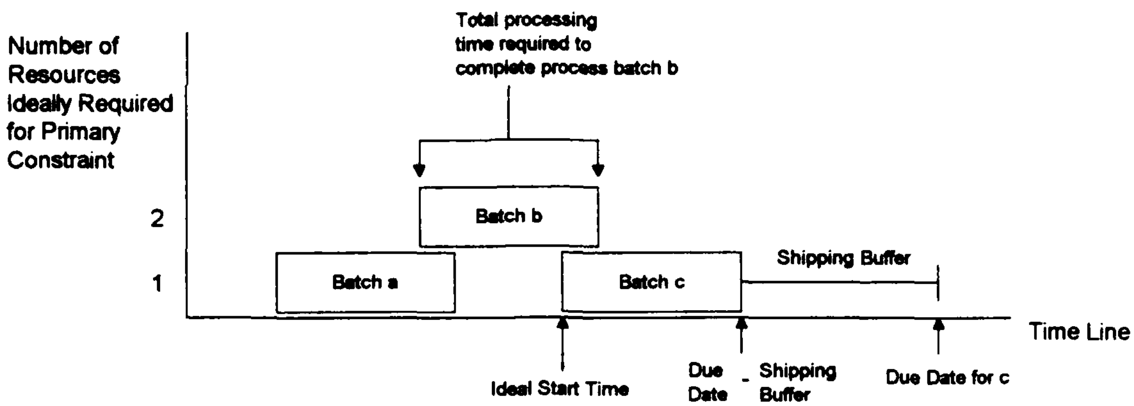


Figure 2: Ruins for Primary Constraint

When a primary constraint process station feeds another primary constraint process station, *DISASTER™* schedules these constraint process stations with what is known as a 'batch rod' between the to constraint process batches. A batch rod is a period of time that is one half the time of a resource constraint buffer. Batch rods protect the second constraint process station from variability caused by intermediate non-constraint process stations. (If there are no intermediate non-constraint process stations between the two constraint process stations, a batch rod is not required.) The batch rod is placed either between the first units in each process batch or between the final units in each process batch. The placement of this batch rod depends upon the processing time per unit for each constraint process station. If the predecessor process station's processing time per unit is greater than the successor process station's processing time per unit, then the batch rod exists between the final units in each process batch. If the predecessor process station's processing time per unit is less than the successor process station's processing time per unit, then the batch rod exists between the first units in each process batch.

As an example of a constraint process station feeding another constraint process station, consider a job order requiring two process stations (A and B) on the constraint resource. Figure 3 identifies an example where a primary constraint process station (A) feeds another (B) in the production operation. Figure 3 identifies four process batches required for two job orders. The final constraint process station (B) for a job order is scheduled first, with its finish time set equal to the due date minus one shipping buffer. In this example, the first constraint process station requires less processing time per unit than the constraint process station it is feeding; therefore, a lesser amount of total processing time is required for the first process batch (A) than the second (B) since each batch contains the same number of units. (The total processing time per batch is identified by the size of the bricks in Figure 3.) Since the processing time per unit on the predecessor process station is less than the processing time per unit on the successor process station, the batch rod exists between the first units in each batch.

At this point in the scheduling algorithm, the ruins display the ideal schedule for the constraint resource, and do not consider any limits on the number of units of that constraint resource which is available. In addition, the ruins will allow for scheduling of process batches before the first day of the time horizon. These discrepancies are resolved in subsequent steps in order to create a feasible schedule.

Backward/Forward Passes. *DISASTER™*'s next step is to calculate a schedule for the constraint resource that resolves any infeasible conditions in the ruins. This new schedule is called the drum schedule. The backward pass accounts for the finite capacity of the resource by 'leveling the ruins.' In effect, process batches that exceed the capacity of the constraint resource are pushed backward in time until the earliest time they can be scheduled without violating any associated batch rods. As a result of this backward 'leveling,' more batches may be scheduled before the first day of the time horizon.

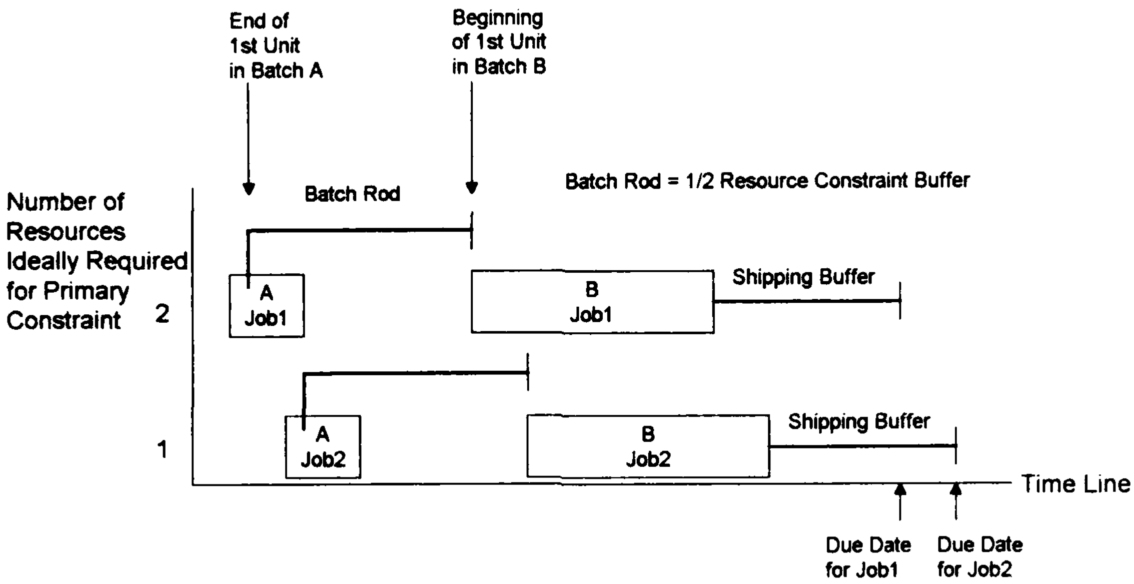


Figure 3: Ruins for Primary Constraint With Interaction

Figure 4 illustrates the leveling of the ruins depicted in Figure 3 as a result of the backward pass. The process batches have been scheduled so as not to violate any of the rods between process batches. This is the reason for the space between process batch A for Job 1 and process batch A for Job 2. Note process batch A for Job 1 has been scheduled to begin into the past.

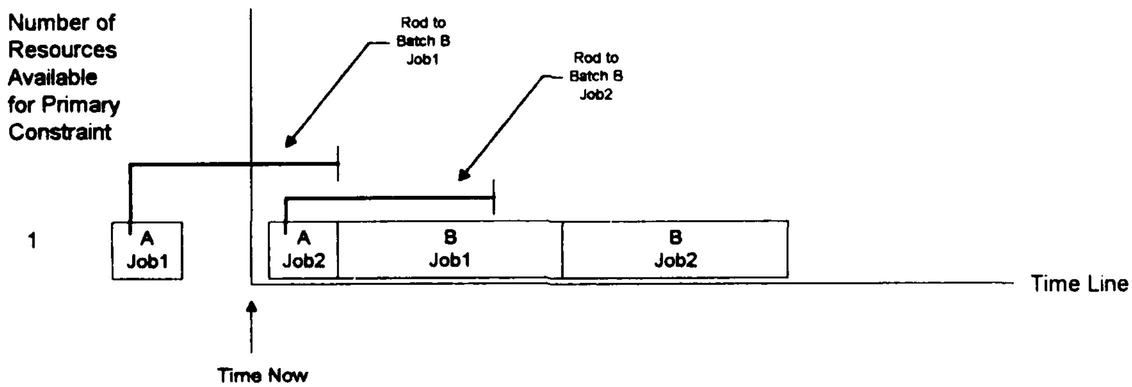


Figure 4: Schedule for Batches After Backward Pass

If the backward pass results in process batches scheduled into the past, a forward pass is required. During the forward pass, the earliest scheduled batch from the backward pass is pushed forward to start on the first day of the time horizon. The remaining process batches are then scheduled from earliest to latest until all time horizon conflicts have been resolved. Once the constraint schedule is established, it is considered fixed in time and can not be altered by further subordination iterations. Figure 5 identifies the batches from Figure 4 after the forward pass. Note process batch A for Job 1 has now been scheduled to begin at the start of the time horizon.

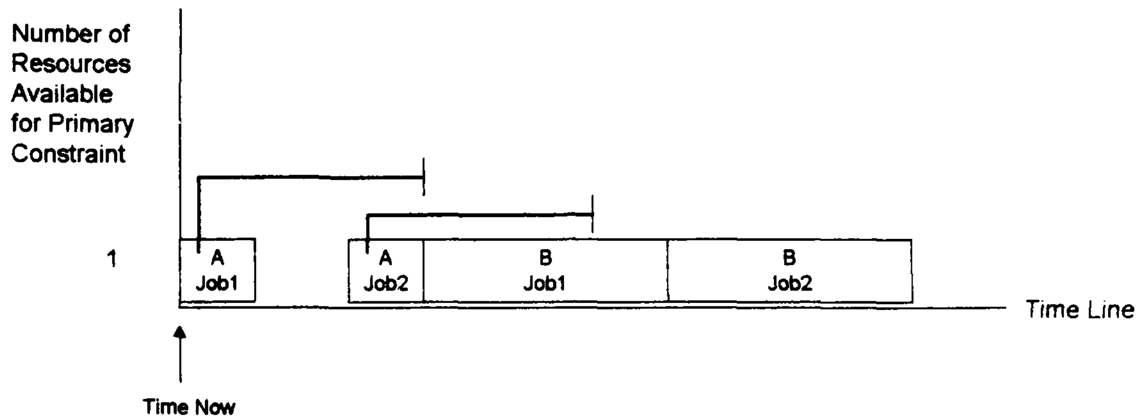


Figure 5: Drum Schedule for Batches After Forward Pass

Subordinate to Primary Constraint. Subordination of the non-constraint resources is reaccomplished to support the schedule developed for the primary constraint resource. Each non-constraint resource is backward scheduled from latest to earliest day in the time horizon. Once again a First Day Load Peak may arise for one of the non-constraint resources. A resource with a First Day Load Peak is treated as a secondary constraint. In addition, for those non-constraint process stations fed by a primary constraint process station, it is possible to push loading on the non-constraint no earlier in time than the previously scheduled start of the primary constraint process station. If loading for a particular non-constraint resource is required before the previously scheduled start of the primary constraint process station, a loading peak exists for this non-constraint resource. *DISASTER™* identifies this as a Red Lane Peak for that particular non-constraint resource. (A 'red lane' is that portion of the production operation which is fed by a resource constraint process station.) As was the case with a First Day Load Peak, a resource with a Red Lane Peak is treated as a secondary constraint.

Secondary Constraint Ruins, Backward/Forward Passes. The process used to establish the primary constraint schedule is repeated for the secondary constraint. The ruins schedule is created for the secondary constraint. As was the case with the primary constraint, *DISASTER™* schedules these secondary constraint process stations with 'batch rods' between the feeding process batches of the secondary constraint. In addition, 'time rods' may now be required. A time rod is a rod one half the size of a resource constraint buffer. Time rods are placed between process batches produced by **different** constraint resources. These process batches feed, or are fed by, one another. In other words, a time rods exists between interactive constraint process batches. Time rods, like batch rods, protect the schedule from variability caused by intermediate non-constraint process stations. However, these new rods are called time rods because they extend from primary constraint process batches which have been previously scheduled in time and cannot be shifted like a secondary constraint process batch. Like the batch rods, time rods exist either between the first units in each process batch or between the final units in each process batch. The secondary constraint schedule must not violate the time rods established by the primary constraint schedule.

Drum Violation and Drum Loop. A situation may arise when establishing the secondary drum (backward/forward passes on the secondary constraint) where the previous constraint's schedule is too restrictive for all time rods to be maintained. In other words, batches from the secondary constraint cannot be scheduled to maintain these time rods. This is referred to as a 'drum violation.' When this occurs, the first constraint's schedule must be revisited and modified to account for these violations. This process is referred to as a 'drum loop.' A drum loop returns to the ruins screen of the first resource constraint and shifts the necessary batches later in time by the amount of time of the violation to resolve the drum violation.

Subordination. If there is a drum loop, all processing performed prior to this new primary constraint ruins schedule is ignored. After the backward/forward passes establishing the modified primary constraint schedule are completed, all remaining non-constraint resources must be subordinated to this modified primary constraint schedule, including the secondary constraint that highlighted the drum violation. Following subordination, it may happen that the secondary constraint is no longer identified as a constraint under the modified primary constraint schedule. However, if a secondary constraint is identified, the entire process is again repeated until a schedule without any violations or peaks is developed.

DISASTER™ Logic in Algorithmic Form. Appendix A contains *DISASTER™*'s logic in algorithmic form for a production operation with two interactive constraints. This algorithm is presented in pseudo-code format and satisfies the first objective of this research effort:

> Research Objective 1: to define the *DISASTER™* scheduling logic in algorithmic form.

The researchers utilized a variety of sources to uncover and document this algorithm. These sources include *The Haystack Syndrome*, *DISASTER™* software and documentation, DBR simulator software developed by the Goldratt Institute, technical documents from the Goldratt Institute, and conversations with Robert Newbold of the Goldratt Institute.

DISASTER™ Limitations

While *DISASTER™*'s logic seems conducive to relatively good production schedules, it would appear to be limited in an environment with interactive constraints. After the specific data about the production environment are input and subordination to the market has occurred, *DISASTER™* identifies the system's constraint(s). If more than one constraint exists, a decision must be made concerning which constraint *DISASTER™* should schedule first. Currently, *DISASTER™* uses a sequential approach; it does not have the capability to schedule multiple constraints simultaneously (Newbold, 1992). *DISASTER™* requires that the scheduler choose the order in which to schedule the constraints. As such, the production schedule produced by *DISASTER™* is dependent upon the order chosen to schedule the constraints. The order chosen "could have significant implications for both the short-term bottom line and the long-term strategy of the company" (Newbold, 1992). If the plant has a certain due date performance management objective, the scheduler must run each constraint order possibility through *DISASTER™* to determine the best production schedule for that objective (Goldratt, 1988:454). However, this schedule still may not be the optimal schedule since *DISASTER™* does not simultaneously schedule multiple constraints nor does it schedule based upon a single specific due date performance management objective. According to Coral Rose of the Avraham Y. Goldratt Institute, companies using *DISASTER™* usually choose the same constraint order every time they develop production schedules (Rose, 1993). This sequence may not produce the best schedule possible from *DISASTER™* in terms of the company's due date performance management objective under the given production environment (set of job orders, resource loading, product types, etc).

Summary

This chapter reviewed relevant literature for this research effort. First, TOC and DBR concepts were defined and described. Next, scheduling criteria were defined, with emphasis placed on job order due date performance as a measure of schedule performance. Finally the *DISASTER™* terminology and scheduling concepts were defined and described. In this section, the first research objective of defining the *DISASTER™* scheduling logic in algorithmic terms was accomplished. The following chapter discusses the methodology used to conduct the remainder of the study.

III. Research Methodology

This chapter describes the methodology used in this study. A method is "a system in doing things or handling ideas" (Neufeldt, 1990:371). In other words, a method is a plan of action for carrying out an idea. This section covers several topics. First, the research design of this study is discussed. Second, the factors chosen for the experiment are reviewed. Third, the background variables that were addressed in the experiment are defined. Finally, the experimental results (dependent variables) reported in Chapter IV and the analysis techniques are defined.

Research Design

Emory and Cooper define research design as "the plan and structure of investigation so conceived as to obtain answers to research questions" (Emory and Cooper, 1992:138). Research design can be divided into the plan for gathering data, the framework for studying the relationships between the study's variables, and the plan for the analysis of data. The research design method chosen for this study was the experimental design.

Experimental Design. According to Emory and Cooper, "experiments are studies whose implementation involves intervention by the researcher beyond that required for measurement." Usually, this intervention involves manipulating one variable in a particular setting, and then observing the reaction of the subject under study (Emory and Cooper, 1992:416). The manipulated variable is defined as the independent variable, and the observed variable is defined as the dependent variable (Moen et al, 1991:63).

Experimental design has several strengths. The primary strength is the fact that the researcher can manipulate the independent variable (Emory and Cooper, 1992:418). This capability increases the probability the researcher can detect whether or not changes in the dependent variable are a function of changes in the independent variable (Emory and Cooper, 1992:418).

The second strength is that the researcher can control background variables more effectively than the researcher could by using other designs (Emory and Cooper, 1992:418). A background variable is a variable that can affect the dependent variable, but is not of interest in the study (Moen et al, 1991:64). This capability gives the researcher greater ability to isolate the independent and dependent variables.

Finally, an experimental design allows the researcher to repeat the experiment multiple times with the independent variable at different levels (Emory and Cooper, 1992:418). This capability allows the researcher more flexibility to generalize the results of the study (Emory and Cooper, 1992:418).

Split-Plot Factorial Design. "The experimental pattern is the schedule for conducting the experiment" (Moen et al, 1991:68). The experimental pattern chosen for this study was a factorial design, in particular the *split-plot factorial design*. In a factorial experiment all levels of all factors are combined with all the levels of every other factor (Hicks, 1973:89). Each of these combinations is called a treatment. The factors are the independent variables of the experiment (Moen et al, 1991:404). The levels are the different populations from which samples are drawn for a factor (Devore, 1991:371). This study looked at the effects of multiple factors, each at multiple levels, on dependent variables.

Factorial designs have two primary advantages over studying one factor at a time. First, a factorial experimental design allows the study of interaction between factors (Moen et al, 1991:115). Interaction occurs when the effect a factor has on the dependent variable depends on the level of a different factor. A researcher is not able to detect the presence of, nor the levels of, interactions when studying the factors one at the time.

The second major advantage of using a factorial design over studying the factors individually is efficiency. When studying one factor at the time, as each new factor is studied, the data already collected is set aside and an entirely new set of data must be collected. Factorial designs allow the researcher to use all of the data collected in the experiment to study each factor.

The split-plot factorial design is a type of repeated measures factorial design (Neter et al, 1990:1035). It is utilized when the same sample of replications or subjects cannot be assigned to each and every treatment (Neter et al, 1990:1066). In this study, there are different replications for each level of **one** of the factors. These replications then receive treatments consisting of each combination of the levels of every other factor. In other words, for the split-plot factorial design, the replications are 'blocked' into the different levels for one of the factors. This factor is said to be completely confounded (Kirk, 1982:490-491). Analysis on the levels of this confounded factor can be accomplished; however, the confounding does affect the precision. The strength of the split-plot factorial design is that large numbers of replications per treatment are not required. Specifically, the split-plot factorial design is appropriate when the number of total treatments is greater than the desired number of replications per treatment. The split-plot factorial design allowed the researchers to generate a manageable number of replications for the benchmark problems within the time limitations imposed for this research effort. Other experimental designs (such as a full factorial experimental design) could not be considered because of the inordinate number of replications required to produce any significant analysis.

Production Variables

The second objective of this research effort was:

Research Objective 2: to develop a set of benchmark problems that represent a diversity of scheduling scenarios with respect to the capabilities of the *DISASTER*™ algorithm.

This research objective is fulfilled in this section.

Defining the production variables for a job shop environment is a difficult task due to the complexity and interaction of the process stations in a job shop. In addition, these variables can be operationalized in infinitely many ways. However, this process of defining and operationalizing the variables aided both the determination of the experimental factors and the determination of background variables.

This section first identifies those production variables chosen as experimental factors. These factors, and their associated levels, are defined and operationalized. After this, the decisions and methods for addressing background variables are defined. The specific background variables for this experiment are then listed, operationalized, and addressed in terms of the development of the benchmark problems.

Experimental Factor 1. Since this study focused on the exploitation of two bottleneck resources (the scheduling of the two drums), an experimental factor specifically defining each bottleneck was desired. Recall that a bottleneck is any resource which has more demand placed on it than it has available capacity. Therefore, a variable which defined the level of demand for each bottleneck was an excellent candidate for an experimental factor. A documented measure of this demand level is the Resource Criticality Factor (RCF) (Gargeya, 1992:3).

Gargeya defines RCF as the "projected workload, relative to capacity for each resource [type] in any given time period" (Gargeya, 1992:3). The RCF for a resource type is given as:

$$RCF = \frac{\text{Total Resource Time Requirement in Given Time Period}}{\text{Number of Units of Resource}}$$

This research experiment operationalized RCF as a percentage, known as percent RCF or %RCF. This factor is:

$$\%RCF = \frac{100\% \cdot RCF}{\text{Total Work Time Available in the Given Time Period}}$$

By operationalizing in this manner, if a resource's %RCF is greater than 100% it has more demand placed on it than it has available capacity for the given time period. Thus this resource is, by definition, a bottleneck. For this research effort, the Given Time Period is the same as the 'time horizon.' The time horizon is a background variable (to be discussed later) and is defined as the length of time from the day the schedule is being generated until the day the last open job order is due.

This experimental factor was tested at three different levels for the lesser constrained of the two constraint resources. (The second experimental factor, described next, establishes the %RCF for the greater constrained of the two constraint resources.) The three levels for %RCF are qualitatively called low, medium, and high. Quantitatively, these levels are summarized in Table 1.

Table 1

Levels of Factor 1, %RCF Lower Constraint Resource

Qualitative Level	Quantitative %RCF (target)	Quantitative %RCF (allowable range)
Low	105%	103-107%
Medium	115%	113-117%
High	125%	123-127%

These target values were chosen to represent situations where a resource's capacity is just below its required capacity (low), where a resource's capacity is far below its required capacity (high), and a situation between these two extremes (medium). The %RCF is also expressed as an allowable range to accommodate the difficulty of operationalizing the factor in terms of simulated processing times. The processing times for each of the lower constraint resource's process stations were calculated to achieve the desired %RCF for the lower constraint resource.

Experimental Factor 2. As previously mentioned, this second experimental factor determined the %RCF for the second (greater constrained) constraint resource. It did so by establishing the percent difference between the two constraints' %RCFs. This factor is the percent delta RCF or %ΔRCF. This factor is operationalized as follows:

$$\%\Delta RCF = \frac{\%RCF_{high} - \%RCF_{low}}{\%RCF_{low}} \cdot 100\%$$

Notice that by establishing the %ΔRCF, the %RCF of the greater constraint resource can be calculated:

$$\%RCF_{high} = \frac{\%\Delta RCF \cdot (\%RCF_{low})}{100\%} + \%RCF_{low}$$

This factor was also tested at three levels. Qualitatively, these three levels are null, low, and high. Quantitatively these levels are summarized in Table 2.

Table 2

Levels of Factor 2, %ΔRCF Between Constraint Resources

Qualitative Level	Quantitative %ΔRCF (target)	Quantitative %ΔRCF (allowable range)
Null	0%	0%
Low	25%	22-28%
High	50%	47-53%

These target values were chosen to represent situations where the two constraints are equally constrained (null), where there is a relatively small difference between the demand placed on the constraints (low), and where there is a substantial difference between the demand placed on the constraints (high). Here, as with %RCF, the low and high levels have an allowable range to facilitate implementation in the simulated environments.

Experimental Factor 3. The third, and final, experimental factor chosen is the type of job shop operation, also known as plant type. Plant types have been categorized by the Goldratt Institute into three varieties: the converging A plant, the diverging V plant, and the assemble-to-order T plant (Newbold, 1992; Fawcett and Pearson, 1991:50). Plants which possess characteristics of more than one of these types are called combination plants (Fawcett and Pearson, 1991:50).

This experimental factor was tested at three levels; each level represented one of the three plant types. Combination plants were not examined in this experiment. The literature which defines and distinguishes between plant types does so only in a qualitative manner. It was therefore necessary to quantitatively operationalize these three plant types into three mutually exclusive experimental factor levels.

The A plant is qualitatively defined as a converging operation, where a large number of component parts or raw materials are assembled into a limited variety of end product types or finished goods (Fawcett and Pearson, 1991:50). For this experiment an A plant was quantitatively operationalized to have the following characteristics:

1) a single predecessor process station never feeds more than one successor process station

2) at least once in the operation, multiple predecessor process stations feed a single successor process station

3) the number of raw materials (RM) must be greater than or equal to three times the number of finished goods (FG)

4) the plant produces a single type of FG

The V plant is qualitatively defined as a diverging operation, where a large number of end product types or finished goods are produced from a relatively small number of component parts or raw materials (Fawcett and Pearson, 1991:50). For this experiment a V plant was quantitatively operationalized to have the following characteristics:

1) at least once in the operation, a predecessor process station feeds more than one successor process station

2) multiple predecessor process stations never feed a single successor process station

3) the number of FG must be greater than or equal to three times the number of RM

4) the plant requires a single type of RM

Finally, the T plant is qualitatively defined as an assemble-to-order operation with a number of common parts used for assembly of the finished goods (Fawcett and Pearson, 1991:51). For this experiment a T plant was quantitatively operationalized to have the following characteristics:

1) all FG are the result of an assembly, where an assembly is defined as multiple predecessor process stations feeding a single successor process station

2) at least once in the final assembly of FG, a single predecessor process station feeds more than one successor (assembly) process station

3) all process stations leading to the component parts which are assembled into FG have a single predecessor process station and a single successor process station (simple flow shop)

A summary of the levels for this factor, plant type, is provided in Table 3.

In order to conduct the experiment on the benchmark problems for all combinations of factors and levels, a total of 3 x 3 x 3, or 27, treatments were examined. Since the factors are the independent variables which were deliberately varied during the experiment, these variables are considered controlled variables. This control over the variables ensured all 27 treatments were obtained.

Table 3

Levels of Factor 3, Plant Type

Qualitative Level	Quantitative Level
A Plant	1) a single predecessor never feeds more than one successor 2) at least once multiple predecessors feed a single successor 3) RM $\geq$ 3 FG 4) a single type of FG produced
V Plant	1) at least once a predecessor feeds more than one successor 2) multiple predecessors never feed a single successor 3) FG $\geq$ 3 RM 4) a single type of RM required
T Plant	1) all FG are the result of an assembly, where an assembly is defined as multiple predecessors feeding a single successor 2) at least once in the final assembly of FG, a single predecessor feeds more than one successor (assembly) 3) all process stations leading to the component parts which are assembled into FG have a single predecessor and a single successor (simple flow shop)

Background Variables and Benchmark Problem Development. Once the experimental factors and levels had been established, the background variables were then defined, operationalized, and addressed. This three-step process ensured that the background variables would not bias the experiment's results. According to Moen, Nolan, and Provost, two decisions must be made regarding background variables in experimental design:

> 1) how to control the background variables so that the effects of the factors are not distorted by them
> 2) how to use background variables to establish a wide range of conditions for the study to increase the degree of belief or to aid in designing a robust product or process
>
> (Moen et al, 1991:70)

In most cases the background variables were controlled for this experiment. There are three methods for controlling background variables:

> 1) hold them constant in the study
> 2) measure them and adjust for their effects in data analysis
> 3) used planned grouping to set up blocks
>
> (Moen et al, 1991:70)

The background variables are next defined and operationalized, and the decisions that were made when addressing each variable are provided. If it was decided the background variable would be controlled, the method for how it was controlled is provided. The final step in developing the benchmark problems was to determine values for each of these background variables. These values are also provided. Once all background variables were defined, operationalized, addressed, and given specific values; the framework for problem development was completed.

Table 4 identifies all background variables addressed in this experiment. The section following Table 4 describes each of the 16 background variables. For each variable there is general description, an operational definition (if required), a statement on how it was addressed in this experiment, and its value(s) for this experiment.

Table 4

Background Variables

Number	Background Variable
1	Type of Available Resources
2	Number of Available Resources
3	Number of Bottlenecks
4	Lower/Higher Constraint Resource
5	%RCF for Non-Constraint Resources
6	Time Horizon
7	Number of Job Orders
8	Size of Job Orders
9	Job Orders and Due Dates
10	Resource Setup Times
11	WIP Inventory Level/Buffer Sizes
12	Total Number of Process Stations/Number of Process Stations per Resource Type
13	Product Types/Location of Constraint Process Stations
14	Location of Non-Constraint Process Stations
15	Percent Protective Capacity for Non-Constraints
16	Scrap/Yield Ratio

__1. Type of Available Resources:__ This variable concerns the different resources available in the plant. For example, resources could be machines or labor. In this study, different resource types are identified by different colors; this is consistent with the *DISASTER*™ manuals and example problems. This variable was controlled by holding it constant at a total of 10 resource types throughout the experiment. These resources were identified as black, white, red, yellow, green, cyan, pink, orange, blue, and gold. All resources were unique and could not be substituted for one another.

2. Number of Available Resources: This variable is the total number of a certain type of resource available in the plant. This variable was controlled by holding it constant throughout the experiment. There was one available resource for each resource type. A single resource was chosen because it presents a more difficult scheduling problem. Having more resources for each resource type makes scheduling the resources easier by giving the scheduler more flexibility (Rose, 1993).

3. Number of Bottlenecks: This variable is the number of resources which have a %RCF greater than 100%. This study addresses only the environment with two interactive constraints. Therefore this variable was controlled by holding it constant throughout the experiment. There were two bottlenecks: the blue and gold resources.

4. Lower/Higher Constraint Resource: This variable determines which constraint's %RCF is lower and which is higher at the different levels for the %RCF and %ΔRCF. This variable was controlled by holding it constant throughout the experiment. The blue resource was always the lower constraint resource as determined by the level of the %RCF factor; the gold resource was always the higher.

5. %RCF for the Non-Constraint Resources: This variable is the percentage of demand relative to capacity for a non-constraint resource. This variable was controlled by holding it constant throughout the experiment. Since this research effort focused on the exploitation of the two bottlenecks, the benchmark problems ensured that the non-constraint resources did not become capacity constraint resources during *DISASTER*™'s subordination process. Therefore the %RCF for the non-constraints was held well below 100% to allow for enough protective capacity. The %RCF for all non-constraints was targeted at 25% (allowable range of 20-30%) and was calculated assuming **no** work-in-process (WIP) inventory existed in the operation.

6. Time Horizon: The time horizon was the length of time of interest. The horizon is defined to span from the current day (the day the schedule is being developed) to the day the last job order is due. This time horizon was used to determine the total available work time for a resource. The experiment assumed a five day, eight hours per day work week. No overtime was allowed. No holidays or down days were assumed. This variable was controlled by holding it constant throughout the experiment. The time horizon was always two weeks. The experiment assumed the job shop schedules every two weeks. The two weeks scheduled in this experiment went from 3 Oct 93 to 16 Oct 93. Note that time horizon and effective horizon as defined by *DISASTER™* are different. The effective horizon defined by *DISASTER™* is the time horizon plus the size of a shipping buffer (*DISASTER™* Manual - Jump Start, 1990:59). *DISASTER™* schedules any required workload in the time horizon for any job orders that become due outside the time horizon, yet inside the effective horizon.

7. Number of Job Orders: This variable is the total number of job orders which become due during the defined time horizon. This variable was controlled by holding it constant throughout the experiment. This experiment assumed that the work required for filling these job orders had not begun at the time the scheduling is taking place. There were 10 job orders outstanding in this experiment.

8. Size of the Job Orders: This variable is the total amount of a product type ordered by a customer. This variable was controlled by holding it constant throughout the experiment. Each order was for a single product type and for a constant quantity of 100 units.

9. Job Orders and Due Dates: This variable is the date a specific job order becomes due. *DISASTER™* does not consider a job order late unless its last constraint process station is scheduled to finish later than the due date minus one half of a shipping buffer (*DISASTER™* Manual - Jump Start, 1990:81). *DISASTER™* uses this logic to identify whether or not a job order is late in the New Order Due Dates Output File (*.SD3). If a job order was identified as being late in this output file, it was considered late for this experiment. There were ten (10) job orders which had to be scheduled for this experiment. Job order due dates were assigned according to the due date assignment rule based on a job order's arrival date and the number of process stations for that job order's product type (Ragatz and Mabert, 1984:29).

Product types produced by the plant type of interest were randomly sampled without replacement, and arrival days from the two work weeks preceding the scheduling date (20 Sep 93 to 1 Oct 93) were randomly sampled with replacement. These two results were then paired together. This pairing continued until all product types had been drawn. The product types were then replaced and the procedure continued until there were 10 job orders with a product type and an arrival date assigned.

Product types were sampled without replacement to allow all product types to be drawn. Sampling without replacement also attempted to equate the number of job orders for each product type. This equality would occur when the number of product types produced by the plant could be divided evenly into 10 (the total number of job orders). Note that in order for all product types to have a job order assigned, the benchmark problems also ensured that there were less than or equal to 10 product types. Arrival dates were sampled with replacement to allow for more than one job order to arrive on the same day.

After this sampling was completed, each job order's arrival day (integer value from 1 to 10 representing workdays from 20 Sep 93 to 1 Oct 93) was multiplied by the number of process stations for that job order's product type. The job order that had the largest computed value for these multiplications was given the tenth workday (15 Oct 93) as its due date. This procedure allowed the time horizon to equal two weeks. The constant factor for the due date assignment rule was calculated from this job order's due date, arrival date, and number of process stations. Then, in accordance with the due date assignment rule, this constant was multiplied by the number of process stations for the other job orders to estimate the job order's flowtime (Ragatz and Mabert, 1984:29). This determined the number of workdays to be added to the job order's arrival date, which in turn yields the job order's due date. If the due date fell before 4 Oct 93 (before the beginning of the time horizon), the flowtime was added twice, simulating the rescheduling of the job order from its previous due date. This process ensured all job orders' due dates' fell within the time horizon.

Since each plant type has different product types with different process stations, the above sampling procedure had to be reaccomplished for each plant type. In addition, job orders and due dates were used to establish a wide range of conditions for the experiment at each plant type. For each plant type, four samplings for job order due dates were accomplished to establish four replications. Since there were three plant types (A plant, T plant, and V plant), this provided 3 x 4, or 12, sets of job order due dates.

10. Resource Setup Times: This variable is the amount of time it takes to change the configuration of a resource (i.e., machine) to perform a different process. This variable was controlled by holding it constant throughout the experiment. Setup time for all resources was zero. Setup time was eliminated because *DISASTER*™'s scheduling logic knows when the same two process stations are scheduled in sequence to eliminate the unnecessary setup. The Carlson-Lettiere algorithm does not allow for this setup savings, so setup time was eliminated.

11. WIP Inventory Level/Buffer Sizes: This variable is the amount of WIP inventory available in the plant. WIP is operationalized in this experiment in terms of the size of the resource constraint buffers. This variable was controlled by holding it constant throughout the experiment. The only WIP allowed in the plant is the WIP required to fill the **first** resource constraint buffer in each leg of the operation and any assembly buffers in the operation. It was assumed that each job shop would attempt to keep these buffers full. Since it was assumed no work had begun to fill the open job orders, no other WIP was allowed. However, the experiment did assume all raw materials required to produce all job orders were available.

According to Umble and Srikanth, a convenient way to calculate the starting point for the **total** time buffer is to use one-half the plant's manufacturing lead time (Umble and Srikanth, 1990:145). In addition, they identify buffer sizes in eight-hour (workday) intervals (Umble and Srikanth, 1990:145). All buffers in each plant's operation (resource, assembly, and shipping) were calculated at less than one day (eight-hours), and so, based upon the Umble and Srikanth guidelines, all buffers were sized as one day (eight-hour) buffers.

12. Total Number of Process Stations/Number of Process Stations per Resource Type: These variables were related in this experiment. The total number is the total number of process stations required in the operation to produce every product type. This variable is an indication of the size of the operation. It was also assumed that every resource is used somewhere in the operation. The number per resource type is the number of process stations (out of the total number) which require a specific resource. These two variables were controlled by holding them constant throughout the experiment. There were 30 total process stations in each plant type, with each of the ten resource types having three process stations (10 resources x 3 process stations = 30 total process stations).

13. Product Types/Location of Constraint Process Stations: This variable identifies the longest sequence of constraint process stations (most interactions) for a given product type. This experiment assumed that all product types must be processed by at least one resource constraint process station. In addition, the resource constraint process stations were never consecutive in the operation. In order to achieve a wide range of conditions, the experiment used various sequences of constraint process stations for the product types. The following table identifies the longest sequences of constraint process stations (most interactions) for each product type in each plant type:

Table 5

Product Type Constraint Interaction

Plant Type	Product Type	Constraint Sequence with Most Interaction
A	FG - D	Blue - Gold - Blue
T	FG - B	Blue - Blue - Gold - Blue
T	FG - C	Blue - Blue - Gold
T	FG - D	Gold
T	FG - F	Gold
T	FG - G	Blue - Blue - Gold - Gold
V	FG - A	Blue - Blue
V	FG - B	Blue - Gold
V	FG - D	Blue
V	FG - E	Gold - Gold
V	FG - G	Gold - Gold - Blue

14. Location of Non-Constraint Process Stations: This variable is the location of the non-constraint process stations within the production operation. Initially for each plant type, after the constraint process stations had been distributed according to the sequences from the previous background variable, the non-constraint process stations were randomly distributed to the remaining process stations. This variable was then controlled by holding it constant throughout the experiment. This distribution is relatively insignificant for this research since all non-constraint's %RCF and number of process stations are equal.

15. Percent Protective Capacity for Non-Constraints: *DISASTER™* allows for the user to identify a percent of the daily load on a non-constraint to withhold from scheduling to protect that resource from daily disruptions. This variable was controlled by holding it constant throughout the experiment. For all problems the percent protective capacity for non-constraints was 5%. This 5% was selected because it represents *DISASTER™*'s minimum allowable protective capacity. Non-constraint protective capacity had already been addressed under variable number five, %RCF for the non-constraint resources.

16. Scrap/Yield Ratio: This variable identifies the amount of material required by a process station from its predecessor station(s) to produce a single unit. Some additional material may be required at a station due to scrap that is produced or the multiple components that are needed. An example of this yield ratio may be seen in the process of producing wagons: the production of one wagon requires four wheels.

Having now defined, operationalized, and addressed all experimental factors (and their levels) as well as the background variables; the environment for developing the benchmark problems is complete. Four replications per plant type (A plant, T plant, and V plant) were developed and held constant at every level of the other two factors, %RCF and %ΔRCF. Since each plant type contained different replications, this factor was the completely confounded variable in this split-plot factorial design. Because of this confounding, the precision of the analysis for this factor will be less precise (Kirk, 1982:491). The other two independent variables, %RCF and %ΔRCF, also had three levels. Thus, the four replications per plant type yielded 3 x 3 x 3 x 4, or 108, benchmark problems. For the outcome of this sampling process which produced the 12 sets of job order due dates (four per plant type) see Appendix B. In addition, a network representation for each of the benchmark problems can be found in Appendix C. There are 27 networks, each one representing an experimental treatment. Associated with each network are the four sets of ten job orders which constitute the replications for that experimental treatment.

Data Collection of Dependent Variables

The data from each replication was scheduled using *DISASTER™* twice, once with the blue constraint (lower %RCF) scheduled as the primary resource constraint, and once with the gold constraint (higher %RCF) scheduled as the primary resource constraint. As a result, *DISASTER™* produced two schedules for each replication which in many cases were not identical.

Data were gathered on certain due date performance measures from both schedules, as well as the percent difference between the two schedules for the due date performance measures. The due date performance objectives measured and analyzed were:

1) total number of days late for the 10 job orders for the best schedule (TDL_{best})

2) the maximum tardiness (in days) of the 10 job orders for the best schedule (MTD_{best})

3) total number of days late for the 10 job orders for the worst schedule (TDL_{worst})

4) the maximum tardiness (in days) of the 10 job orders for the worst schedule (MTD_{worst})

5) the percent difference between the two schedules for total number of days late of the 10 job orders (%DIFFTDL)

6) the percent difference between the two schedules for maximum tardiness (in days) of the 10 job orders (%DIFFMTD)

These data are the dependent, or response, variables.

The best schedule was defined as the schedule that best met the due date performance objective being measured for that particular replication. For example, if total days late was being measured, the schedule that had the least number of total days late was the best schedule. The worst schedule was defined as the schedule that had the worst performance for the due date performance objective being measured for that particular replication. For example, if maximum tardiness (in days) was being measured, the schedule that had the most tardy job order was the worst schedule.

The percent difference between the best and the worst schedule for each replication was computed for both the total number of days late and maximum tardiness. The percent differences were defined as follows (using total days late as the example):

$$\%\mathrm{DIFFTDL} = \frac{\mathrm{TDL}_{worst} - \mathrm{TDL}_{best}}{\mathrm{TDL}_{best}} \cdot 100\%$$

TDL_{best} and MTD_{best} were measured as dependent variables for three reasons. First, these measures were used to verify that the three experimental factors and their associated levels produced a diversity of scheduling scenarios. Second, these measures can be used to compare alternative scheduling algorithms which use the same scheduling scenarios (benchmark problems) as input. Third, collection of this data was necessary in order to calculate %DIFFTDL and %DIFFMTD.

TDL_{worst} and MTD_{worst} were measured as dependent variables for two reasons. First, TDL_{worst} and MTD_{worst} were used in conjunction with TDL_{best} and MTD_{best} in order to evaluate whether or not the constraint sequence chosen affected the due date performance of *DISASTER™* across all 108 replications. Second, collection of this data was necessary in order to calculate %DIFFTDL and %DIFFMTD.

The final two dependent variables (%DIFFTDL and %DIFFMTD) were obtained for one reason. These variables were used to determine if there were any differences in %DIFFTDL or %DIFFMTD across the levels of the three experimental factors when different constraint sequences were chosen. In other words, the results would show if the constraint sequence chosen has a greater impact on due date performance at different levels of the three factors.

Type of Analysis for Experimental Results

Analysis of variance (ANOVA) was the method chosen to fulfill Research Objective Four. Research Objective Four is the evaluation of *DISASTER*™'s due date performance as the levels of the factors change to ensure the benchmark problems produce a diversity of scheduling scenarios. ANOVA is a statistical method for testing a null hypothesis that the true means (μ's) from multiple populations are equal (Emory and Cooper, 1992:547). The results of ANOVAs for TDL_{best} and MTD_{best} determined whether or not a wide diversity of scheduling scenarios was achieved with respect to these performance measures. ANOVA was used to ascertain whether or not there were any differences among the true means based on the samples associated with the different levels of the three factors. If ANOVA suggested differences among the true means existed, the benchmark problems generated did create a diversity of scheduling scenarios.

ANOVA was also used to ascertain if there were any interactions among combinations of these three factors. When interaction exists, the value of the dependent variable at one level of a factor depends upon the level of another factor (Neter et al, 1990:232). If the ANOVA suggested interaction(s) existed, the researchers analyzed the effect of the interaction. The analysis was accomplished "by examining whether the treatment mean curves for the different factor levels in a graph are parallel" (Neter et al, 1990:685). If these graphs are not perfectly parallel, interaction does exist. However, sometimes the interaction effects are so small they are considered to be unimportant interactions (Neter et al, 1990:687). Unimportant interactions can be disregarded and the analysis of factor effects can continue as if there was no interaction (Neter et al, 1990:687). According to knowledgeable statisticians, determining whether interactions are important is a subjective assessment of the treatment mean curves for the different factor levels. The interaction effects can be considered unimportant at the given levels of the factors if the treatment mean curves are relatively parallel and do not intersect (Reynolds, 1993).

In addition, ANOVA was used to fulfill Research Objective Five. Research Objective Five is the determination of the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences. The results of ANOVAs for %DIFFTDL and %DIFFMTD determined the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences across the different levels of the three factors.

ANOVA Model. The ANOVA model used to conduct this research was the split-plot ANOVA model. The mathematical representation for the model is as follows:

$$Y_{ijkm} = \mu + \alpha_j + \pi_{i(j)} + \beta_k + (\alpha\beta)_{jk} + (\beta\pi)_{ki(j)} + \gamma_m + (\alpha\gamma)_{jm} + (\gamma\pi)_{mi(j)} + (\beta\gamma)_{km} + (\alpha\beta\gamma)_{jkm} + (\beta\gamma\pi)_{kmi(j)} + \varepsilon_{ijkm}$$

where:

Y_{ijkm} = the random variable denoting the measurement of the dependent variable where factor A is held at level j (j = 1, 2, 3), factor B is held at level k (k = 1, 2, 3), and factor C is held at level m (m = 1, 2, 3) for the i^{th} replication (i = 1, 2, 3, 4)

μ = the overall population mean

α_j = the effect of factor A at level j

$\pi_{i(j)}$ = the effect of replication i nested within level j of factor A

β_k = the effect of factor B at level k

γ_m = the effect of factor C at level m

$(\alpha\beta)_{jk}$, $(\alpha\gamma)_{jm}$, and $(\beta\gamma)_{km}$ = two-factor interaction parameters

$(\alpha\beta\gamma)_{jkm}$ = three-factor interaction parameters

$(\beta\pi)_{ki(j)}$, $(\gamma\pi)_{mi(j)}$, $(\beta\gamma\pi)_{kmi(j)}$ = the joint effects of the treatment levels k, m for factors B and C respectively with replication i nested within level j of factor A

ε_{ijkm} = the experimental error

(Kirk 1982:495,536)

Hypotheses Tested in ANOVA. For each dependent variable, Y_{ijkm}, the following hypotheses are tested in the ANOVA model. (For Research Objective Four, Y_{ijkm} was TDL_{best} and MTD_{best}. For Research Objective Five, Y_{ijkm} was %DIFFTDL and %DIFFMTD.)

1) H_O: all α_j's = 0
   H_a: at least one $\alpha_j \neq 0$

2) H_O: all β_k's = 0
   H_a: at least one $\beta_k \neq 0$

3) H_O: all γ_m's = 0
   H_a: at least one $\gamma_m \neq 0$

4) H_O: $(\alpha\beta)_{jk} = 0$
   H_a: $(\alpha\beta)_{jk} \neq 0$

5) H_O: $(\alpha\gamma)_{jm} = 0$
   H_a: $(\alpha\gamma)_{jm} \neq 0$

6) H_O: $(\beta\gamma)_{km} = 0$
   H_a: $(\beta\gamma)_{km} \neq 0$

7) H_O: $(\alpha\beta\gamma)_{jkm} = 0$
   H_a: $(\alpha\beta\gamma)_{jkm} \neq 0$

All seven of these hypotheses were tested for each ANOVA in this study. The level of significance for these hypothesis tests was always $\alpha = 0.05$.

Assumptions of ANOVA. There are certain assumptions associated with ANOVA. First, the populations sampled are assumed to be normally distributed. In the ANOVA model, this assumption is identified by normality of the error terms. Second, the variance of the distributions of the populations sampled are assumed equal. In the ANOVA model, this assumption is identified by constant scatter of the residuals for all replications. Third the observations from each factor level are random observations and are independent of the observations for any other factor level. In the ANOVA model this assumption is identified by independence of the error terms (Kirk, 1982:75). Finally, although not necessarily an assumption, when using ANOVA each treatment must have the same number of replications, otherwise the analysis would become overly complicated (Devore, 1991:374).

In order to assess the assumption of normality, the residuals were analyzed to determine if they were normally distributed. This analysis was accomplished using normal probability plots and Wilk-Shapiro test statistics (Shapiro and Francia, 1972:215-216). A probability plot which appears linear suggests the sample was drawn from a normally distributed population. A Wilk-Shapiro test statistic of 0.995 for the sample size in this study (sample size = 108) would not allow one to reject the normal distribution as the population distribution at a level of significance of $\alpha = 0.05$ (Shapiro and Francia, 1972:215-216). However, knowledgeable statisticians recommend a less stringent heuristic of 0.9 for the Wilk-Shapiro test statistic (Miller, 1993; Reynolds, 1992). In addition, for ANOVA, "lack of normality is not an important matter, provided the departure from normality is not of extreme form" (Neter et al, 1990:623). Therefore the researchers applied the 0.9 heuristic for the Wilk-Shapiro test statistic when analyzing the residuals.

As for the assumption of equal variances, since this study had an equal number of replications for each treatment, "there is little reason to test the homogeneity of variance assumption" (Kirk 1982:78). However, the researchers chose to verify this assumption for good measure. To determine constancy of variance, a scatter plot of the residuals versus the fitted values of the ANOVA model was developed (Neter et al, 1990:609-610). When the error variance is constant, these plots should show the same extent of scatter for all of the residuals.

The assumption of independence was addressed by utilizing the split-plot ANOVA model for the analysis. The split-plot ANOVA model views the effects of the replications as random, and therefore independent, if the replications are randomly sampled (Neter et al, 1990:1037). In this study, the replications for each plant type were randomly sampled as discussed earlier in this chapter.

Statistical Procedure to Test Hypotheses. An *f* statistic was calculated for each factor and every possible combination of factors using standard statistical procedures (Kirk, 1982:540; Devore, 1991:422-428). Each single factor is known as a main effect, and every combination is known as an interaction. For example, if the experiment consisted of factors A, B, and C; an *f* statistic would be found for A, B, C, AB, AC, BC, and ABC.

This *f* statistic is compared to a critical *F* value found using the appropriate degrees of freedom and desired level of significance. If the *f* statistic is less than the critical *F* value, the null hypothesis cannot be rejected and the researchers must conclude all of the true averages of the populations of the given main effect or interaction at the different levels are not considered significantly different at the given level of significance.

Should the *f* statistic be greater than the critical *F* value, at least one of the true averages of the populations of the given main effect or interaction at the different levels is statistically different from the others. Should this be the case, further analysis is needed to determine which of the populations is statistically different from the others. This analysis requires multiple comparisons of means. In particular, this study was concerned with multiple pairwise comparisons. Pairwise comparisons only analyze the means of two factor levels for a statistically significant difference. All pairwise comparisons of interest for a given factor constitute the family of comparisons. A level of significance for this family of comparisons must be selected. This selection determines the level of significance for all multiple comparisons made. Tukey's procedure is the method of multiple comparisons to be utilized when the family of interest is the set of all pairwise comparisons of factor level means (Neter et al, 1990:580).

Tukey's Procedure. Tukey's procedure uses the probability distribution called the studentized range distribution. The critical value is found using the appropriate degrees of freedom and level of significance. Once this value is found, it is multiplied by a constant, and then it is determined which sample mean(s) differ by more than this constant. The sample mean(s) that differ by more than this constant are found to be statistically different from the others. Since contrasts or linear combinations for factor level means were not of interest in this study, Tukey's procedure was chosen over both Scheffé and Bonferroni methods. Tukey's procedure is superior to both of these methods when all pairwise comparisons are the only comparisons of interest since Tukey's procedure provides narrower confidence limits (Neter et al, 1990:587,589).

ANOVA in this Experiment. Table 6 identifies each variable of the ANOVA model for this experiment. This study used ANOVA to analyze any significant differences (or absence of significant differences) in the means for TDL_{best} and MTD_{best} across all factors and their associated levels. This ANOVA showed if a diversity of scheduling scenarios was achieved and if any interaction existed among experimental factors. In addition, ANOVA for %DIFFTDL and %DIFFMTD was used to analyze the extent to which *DISASTER*™'s due date performance is affected by a different constraint scheduling sequences across the different levels of the three factors.

Table 6

ANOVA Model Variables for this Experiment

ANOVA Model Variable	Variable in this Experiment
Y	TDL_{best}, MTD_{best}, %DIFFTDL, or %DIFFMTD
A	plant type
B	%RCF
C	%ΔRCF
i	number of replications for each treatment (4 replications)
j	levels for plant type (A, V, T)
k	levels for %RCF (105%, 115%, 125%)
m	levels for %ΔRCF (0%, 25%, 50%)

Summary

This section reviewed the methodology of the study. First, the split-plot factorial experimental design was reviewed. The factors and the levels of the factors used in this experiment were then operationalized. The factors for this experiment are the %RCF of the lowest constraint, the %ΔRCF between the highest and the lowest constraint, and the plant type. In this split-plot factorial design, plant type was the completely confounded factor. The background variables were then defined, operationalized, and addressed. Next, the dependent variables were defined and discussed. The dependent variables included in the results are total number of days late for the best schedule (TDL_{best}), maximum tardiness (in days) for the best schedule (MTD_{best}), total number of days late for the worst schedule (TDL_{worst}), maximum tardiness (in days) for the worst schedule (MTD_{worst}), the percent difference between the total days late for the best and the worst schedule for each replication (%DIFFTDL), and the percent difference between the maximum tardiness for the best and the worst schedule for each replication

(%DIFFMTD). Finally, the analysis technique used in this experiment (ANOVA) was discussed. Figure 6 displays a flowchart which summarizes the methodology in this experiment. The next chapter reports, analyzes, and discusses the results of the experiment.

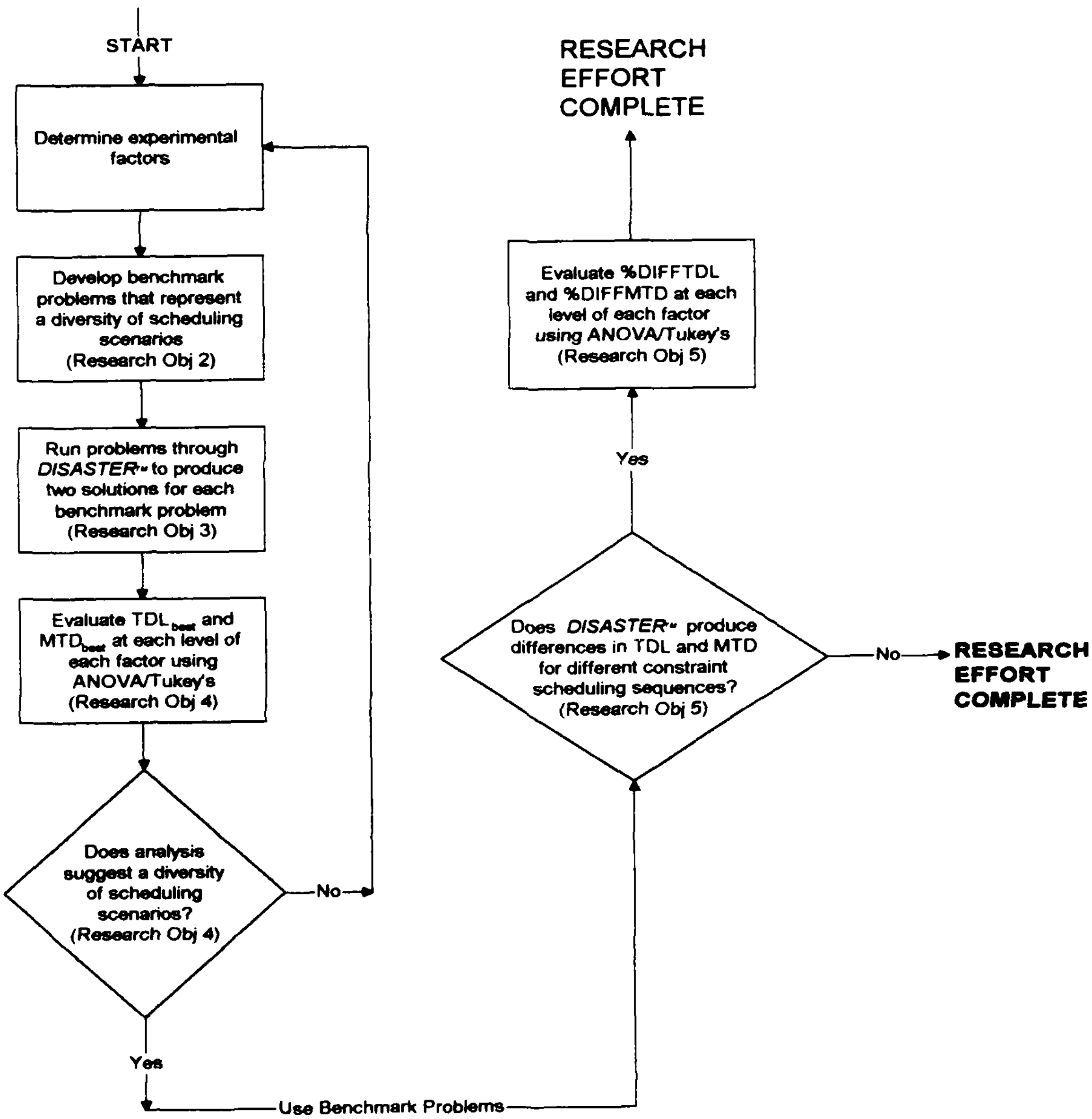


Figure 6: Methodology Flowchart

IV. Findings

Overview

Three of the five research objectives of this study are addressed in this chapter. The three objectives to be addressed are:

Research Objective 3: to produce solutions (schedules) for the benchmark problems using the *DISASTER™* software

Research Objective 4: to evaluate *DISASTER™*'s due date performance as the levels of the factors change to ensure the benchmark problems produce a diversity of scheduling scenarios

Research Objective 5: to determine the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences.

This chapter is structured to address these three research objectives one at a time. Research Objective Three is addressed by reviewing how the experiment was accomplished. Research Objective Four is addressed by discussing the findings of the ANOVAs performed on TDL_{best} and MTD_{best}. Research Objective Five is first addressed by determining the percentage of the 108 benchmark problems where TDL_{best} did not equal TDL_{worst}, as well as where MTD_{best} did not equal MTD_{worst}. Research Objective Five is next addressed by discussing the findings of the ANOVAs performed on %DIFFTDL and %DIFFMTD. Finally, after these objectives are addressed the researchers review some of the insights from the experiment and discuss some of the nuances involved with using *DISASTER™*.

How the Experiment Was Accomplished

Research Objective Three, which was to produce solutions (schedules) for the benchmark problems using the *DISASTER™* software, was met by actually conducting the experiment described in Chapter III. To reiterate, this was a split-plot factorial design with three factors which were %RCF, %ΔRCF, and plant type. Plant type was a confounded variable that contained four replications at each level. Each factor had three levels, and each possible combination of the three factors at each of their three levels had four replications resulting in 3 x 3 x 3 x 4 = 108 replications. Each of the 108 replications was run through *DISASTER™* twice, once with the gold bottleneck scheduled first and once with the blue bottleneck scheduled first. This resulted in 216 sets of output files from *DISASTER™*.

When *DISASTER™* was run for each of the replications, the external market was always chosen by the researchers as the first constraint. After the researchers allowed *DISASTER™* to subordinate with the market as the constraint, both the blue and the gold bottleneck would be reported as a constraint by *DISASTER™* because these were the only two resources in the plants loaded beyond their available capacity. The other resources had enough protective capacity so as not to be identified as constraints.

The researchers first allowed *DISASTER™* to run with the bottleneck it recommended to obtain the first schedule for that replication. The researchers then forced *DISASTER™* to run with the other bottleneck as the primary resource constraint to produce the second set of output files for each replication. In this manner the researchers produced the 216 sets of output files. The results, including a record of the constraint *DISASTER™* chose first for each replication, can be found in Appendix D. Later, in the section *Decision Rules for Selecting the Primary Constraint*, the researchers report the percentage of times *DISASTER™* recommended the primary constraint which led to the schedule with the best due date performance.

Identifying Interactive Constraints. In some replications, when the higher loaded bottleneck (gold resource) was scheduled first, the other bottleneck (blue resource) was never identified as a constraint. In other words, this schedule did not produce interactive constraints. The data summary in Appendix D identifies when there was interaction (identification of both the gold and blue resources as constraints) for the benchmark problems.

This phenomenon was caused by the following events. As the %ΔRCF increased, the load on the higher loaded constraint (gold resource) increased. This increased the total processing time for each process batch on the gold resource. (Meanwhile, the total processing time for each process batch on the blue resource remained the same.) Once the ruins were leveled and the gold resource was scheduled, it established the drum for the rest of the resources. As %ΔRCF increased and the total processing time for each process batch increased, the drum established by the gold constraint increased the time between the start time of the batch rod linked to the predecessor process batch and the start time of the successor process batch. This increased the available processing time for those process stations between these gold process stations. This allowed enough time for the process stations between the gold process stations to be completed without any other resources being identified as constraints.

For example, Figure 7 identifies a situation when the total processing time for the gold constraint process batches was small due to small %ΔRCF. This figure represents a drum schedule. It contains two interactive process stations (Process Batch A feeding Process Batch B) for two job orders (Job Order 1 and Job Order 2). Note the length of time between the start time of the batch rod linked to Process Batch A for Job Order 1 and the start time of Process Batch B for Job Order 1. The size of this gap represents the amount of time available for the batch to be processed on intermediate process stations (including the blue process station).

Figure 8 identifies the situation where the total processing time for the gold constraint process batches is larger due to a larger %ΔRCF. Note the length of time between the start time of the batch rod linked to Process Batch A for Job Order 1 and the start time of Process Batch B for Job Order 1 has increased. This allowed enough time for the process stations between the gold process stations to be completed without any other resources being identified as constraints.

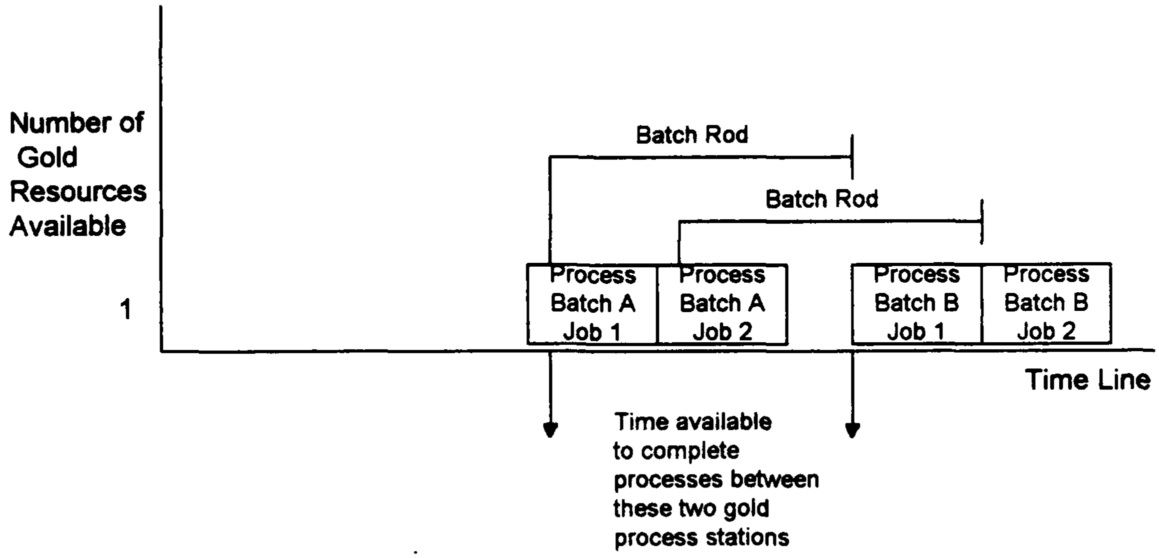


Figure 7: Drum with Small %ΔRCF

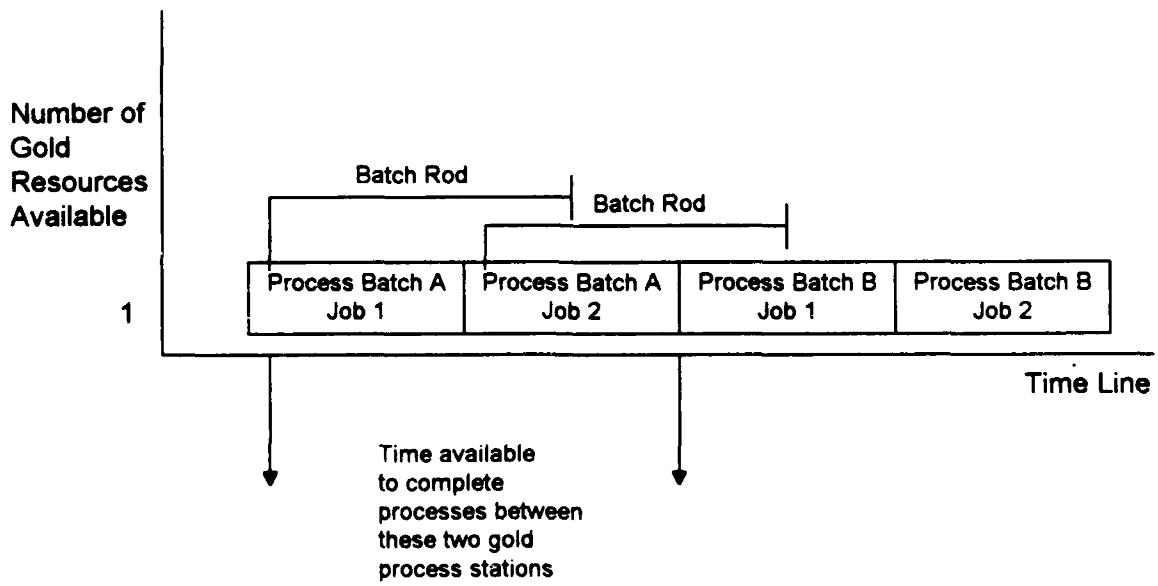


Figure 8: Drum with Large %ΔRCF

Analysis of Due Date Performance

This section addresses Research Objective Four, which is to evaluate *DISASTER™*'s due date performance as the levels of the factors changed to ensure the benchmark problems produced a diversity of scheduling scenarios. The researchers analyzed two due date performance objectives: TDL_{best} and MTD_{best}. Summary tables from *DISASTER™*'s output for the data used in these analyses can be found in Appendix D.

ANOVA was used to determine if there were any statistically significant differences in the means of the levels of the factors. If significant differences in the means were found, Tukey's studentized range test was used to determine which mean(s) was significantly different from the other means. The researchers used the *STATISTIX™* 4.0 software running on a 386DX 40MHz personal computer to perform the analyses.

Assumptions of ANOVA Addressed. Before the ANOVAs were performed, the researchers had to address the assumptions of this analysis technique. The assumption of independence was met by using the split-plot ANOVA model on the experimental results (Neter et al, 1990:1037). The assumptions of normality and constant variance were evaluated using probability plots, Wilk-Shapiro test statistics, and scatter plots of the residuals. The assumptions were verified for TDL_{best} and MTD_{best}. The results of this evaluation can be found in Appendix E.

Total Days Late. Table 7 is the ANOVA table for TDL_{best}. The table identifies seven P-values corresponding to the seven hypothesis tests conducted in the ANOVA. At a level of significance of $\alpha = 0.05$, the ANOVA table suggests two of the interaction terms (plant type * %ΔRCF and %RCF * %ΔRCF) are statistically significant. The remaining interaction terms are not statistically significant. The researchers examined the treatment mean curves for these two interaction terms. The treatment mean curves can be found in

Appendix F. The researchers determined the interaction terms to be unimportant for the analysis. Therefore, the researchers disregarded the interactions and proceeded to analyze any significant factor effects.

The ANOVA table also suggests there are statistically significant differences in some of the means for the levels of %RCF and %ΔRCF. However, plant type was not identified as having statistically significant differences. Although this ANOVA identified that statistically significant differences in the means among the levels of %RCF and %ΔRCF **exist**, it does not identify **which** means have the statistically significant differences for each factor. Therefore, the researchers performed Tukey's procedure of multiple comparisons for %RCF and %ΔRCF.

Table 7

ANOVA Table for TDL_{best}

ANALYSIS OF VARIANCE TABLE FOR BESTTDL

SOURCE	DF	SS	MS	F	P
PLANT	2	2288.22	1144.11	0.79	0.4848
REP					
PLANT*REP	9	13110.0	1456.66		
%RCF	2	2666.00	1333.00	398.42	0.0000
PLANT*%RCF	4	24.4444	6.11111	1.83	0.1677
PLANT*REP*%RCF	18	60.2222	3.34567		
%ΔRCF	2	8400.16	4200.08	300.34	0.0000
PLANT*%ΔRCF	4	714.777	178.694	12.78	0.0000
PLANT*REP*%ΔRCF	18	251.722	13.9845		
%RCF*%ΔRCF	4	79.1666	19.7916	11.08	0.0000
PLANT*%RCF*%ΔRCF	8	17.8888	2.23611	1.25	0.2984
PLANT*REP*%RCF*%ΔRCF	36	64.2777	1.78549		
TOTAL	107	27676.9			

Tukey's Results for %RCF. The Tukey's studentized range test was used to determine which means were statistically different for %RCF. This test suggested that the mean TDL_{best} for each level of %RCF was significantly different from the mean at the other two levels at a family level of significance of $\alpha = 0.05$. The results of the Tukey's studentized range test can be found in Appendix F.

Figure 9 displays the means for TDL_{best} for the three levels (low, medium, high) of %RCF as well as the mean for all 108 replications (grand mean) as calculated in the Tukey's studentized range test. Figure 9 identifies that as the %RCF is increased, the mean TDL_{best} increased. As the loading on the plant's critical resources (bottlenecks) is increased, one would expect the job orders to become more and more late since the bottlenecks control the throughput of the entire plant. The benchmark problems performed as expected.

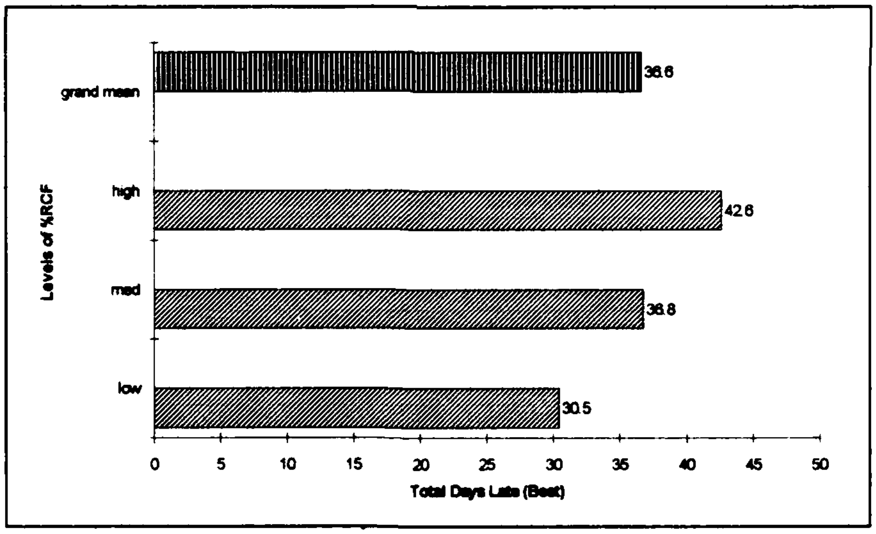


Figure 9: Mean TDL_{best} versus %RCF

Tukey's Results for %ΔRCF. The Tukey's studentized range test suggested that the mean for TDL_{best} for each level of %ΔRCF was significantly different mean curves for these two interaction terms. The treatment mean curves can be found in Appendix G. The researchers determined the interaction terms to be unimportant for the analysis. Therefore, the researchers disregarded the interactions and proceeded to analyze any significant main effects.

The ANOVA table also suggests there are statistically significant differences in some of the means for the levels of %RCF and %ΔRCF. Once again, plant type was not identified as having statistically significant differences. The researchers performed Tukey's procedure of multiple comparisons for %RCF and %ΔRCF.

Table 8

ANOVA Table for MTD_{best}

ANALYSIS OF VARIANCE TABLE FOR BESTMTD

SOURCE	DF	SS	MS	F	P
PLANT	2	102.796	51.3981	2.04	0.1855
REP					
PLANT*REP	9	226.416	25.1574		
%RCF	2	84.7962	42.3981	654.14	0.0000
PLANT*%RCF	4	0.25925	0.06481	1.00	0.4332
PLANT*REP*%RCF	18	1.16666	0.06481		
%ΔRCF	2	401.851	200.925	493.18	0.0000
PLANT*%ΔRCF	4	3.03703	0.75925	1.86	0.1608
PLANT*REP*%ΔRCF	18	7.33333	0.40740		
%RCF*%ΔRCF	4	6.70370	1.67592	25.86	0.0000
PLANT*%RCF*%ΔRCF	8	1.40740	0.17592	2.71	0.0189
PLANT*REP*%RCF*%ΔRCF	36	2.33333	0.06481		
TOTAL	107	838.101			

Tukey's Results for %RCF. The Tukey's studentized range test suggested that the mean for MTD_{best} for each level of %RCF was significantly different from the mean at the other two levels at a family level of significance of $\alpha = 0.05$. The results of the Tukey's studentized range test can be found in Appendix G. Figure 11 displays the means for MTD_{best} for the three levels (low, medium, high) of %RCF as well as the grand mean as calculated in the Turkey's studentized range test. Figure 11 identifies that as the %RCF is increased, the mean MTD_{best} increased. For the same reasons offered for TDL_{best}, the benchmark problems performed as expected.

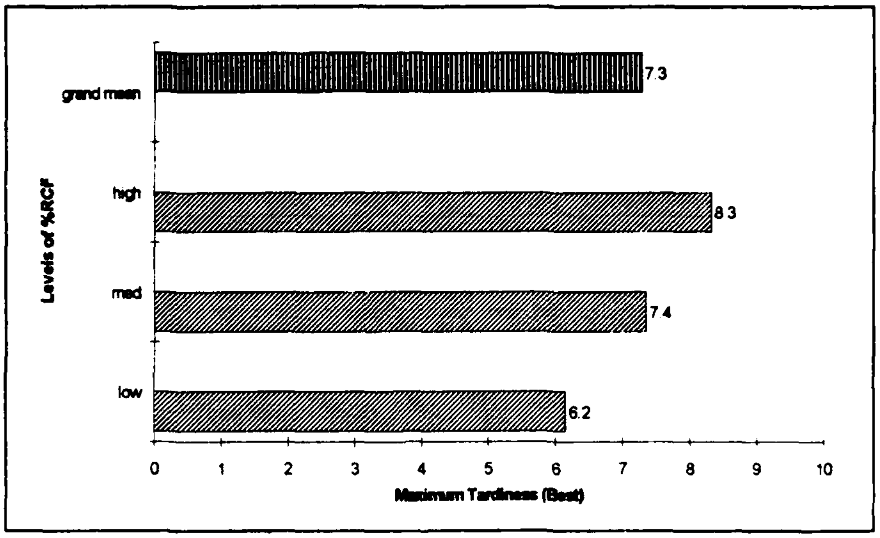


Figure 11: Mean MTD_{best} versus %RCF

Tukey's Results for %ΔRCF. The Tukey's studentized range test suggested that the mean for MTD_{best} for each level of %ΔRCF was significantly different from the mean at the other two levels. The results from the Tukey's studentized range test can be found in Appendix G. Figure 12 displays the means for MTD_{best} for the three levels (null, low, high) of %ΔRCF, as well as the grand mean. Figure 12 identifies that as the %ΔRCF is increased, the mean MTD_{best} increased. For the same reasons offered for TDL_{best}, the benchmark problems performed as expected.

Since there were statistically significant differences among all three levels for both %RCF and %ΔRCF, the results from ANOVA and the Tukey's procedures suggest the benchmark problems do produce a diversity of scheduling scenarios for MTD_{best}.

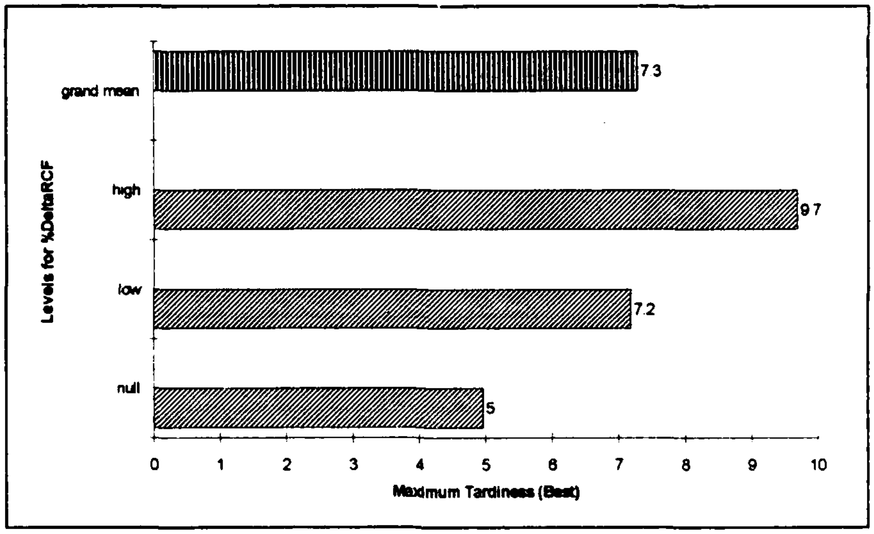


Figure 12: Mean MTD_{best} versus %ΔRCF

The results from these two ANOVAs fulfill the requirements for Research Objective Four. The benchmark problems do produce a diversity of scheduling scenarios for both TDL_{best} and MTD_{best}. As the levels for both %RCF and %ΔRCF change, statistically significant differences for both due date performance objectives are achieved. Plant type is the completely confounded variable in the split-plot factorial design. Since the plant types produced different product types, they required different job order due dates when developing replications. Therefore it is much more difficult for the ANOVA model to identify any statistically significant differences among the means associated with the different levels (plants types) due to the variations caused by the replications.

However, the researchers gained some intuition concerning the different plant types and believe this factor may cause differences in the due date performance of *DISASTER™* that are not detected by this particular experimental design (split-plot factorial design). Figure 13 and Figure 14 identify the means for TDL_{best} and MTD_{best} for the three levels (A plant, T plant, and V plant) of plant type as well as the grand mean.

Notice the mean for the A plant was lower than the other two plant type means for both due date performance measures.

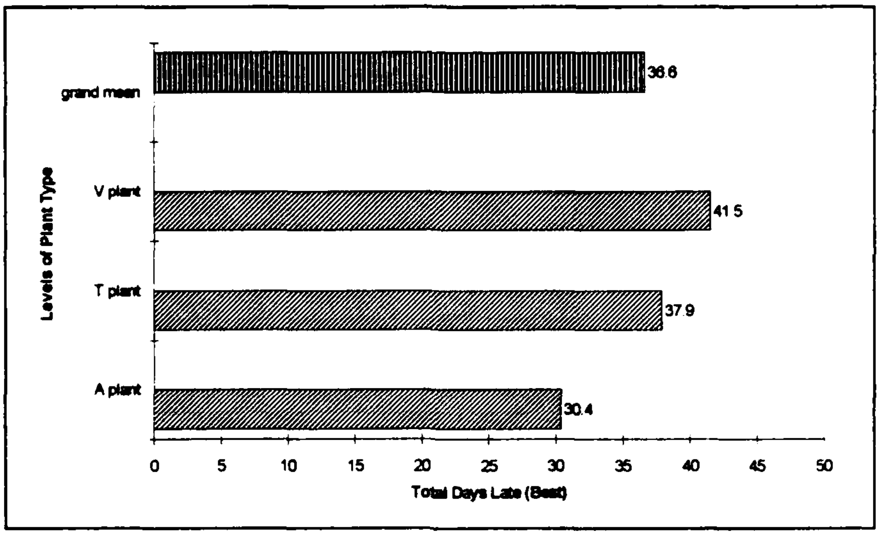


Figure 13: Mean TDL_{best} versus Plant Type

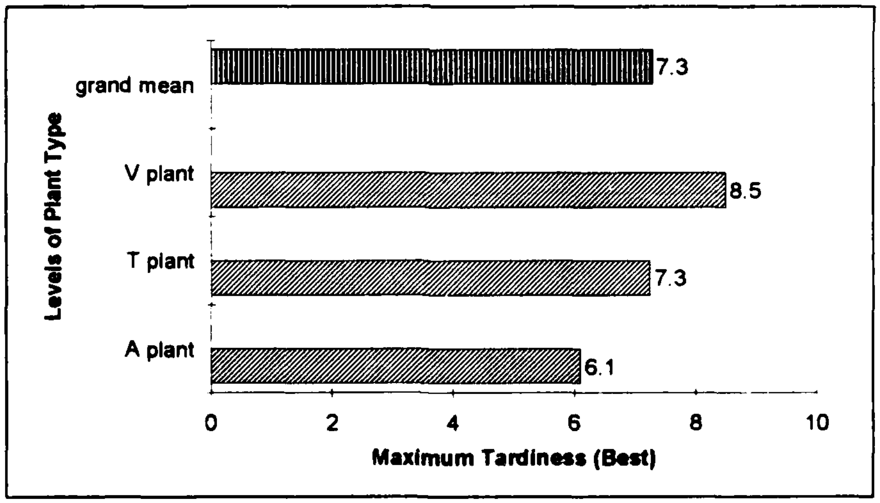


Figure 14: Mean MTD_{best} versus Plant Type

The researchers believe plant type may affect the due date performance of *DISASTER™* after studying the **DISPLAY RODS SCREEN** in the software. Since only one product type was made in the A plant, every bottleneck process station (each of the six) was required to make the one product type. Therefore, more process batches were required (in relation to the other plant types' batches) in order to achieve the desired loading. This led to smaller total processing times per batch for the A plant. On the other hand, the V plant and the T plant made multiple product types and each product type required processing on less than the total number of bottleneck process stations. Thus, to get the same loading (%RCF, %ΔRCF) in each type of plant, different numbers of batches (and therefore different total processing times per batch) were required in the benchmark problems. The smallest total processing time per batch was in the A plant, and the largest total processing time per batch was in the V plant. The smaller total processing time per batch and more batches in the A plant allowed *DISASTER™* more flexibility in scheduling. Thus, *DISASTER™* was able to yield schedules with better due date performance for TDL_{best} and MTD_{best} in the A plant problems.

In addition, the A plant was the only plant type to have constraint process batches with total processing time smaller than the length of a batch rod. This relationship may also have an effect on the A plant's superior due date performance of *DISASTER™* for TDL_{best} and MTD_{best}. This allowed enough time for the process stations between the constraint process stations connected by the rod enough time to be completed without any other resources being identified as constraints. To highlight this situation, Figure 15 displays the total processing time per batch for each plant type relative to the constant length of a batch rod. Since the length of batch rods are dependent only on the size of the constraint buffer and the constraint buffer was the same size throughout the plants, the batch rods were equal in every plant. Figure 15 represents process batches on the gold and blue resources at 105% %RCF and 0% %ΔRCF.

It is important to understand that this reasoning is the researchers' insight and is not supported by this experimental design. The insight gained by examining the benchmark problems in detail, however, leads the researchers to suspect that an experimental design in which plant type is not confounded might determine this to be a significant factor for these performance measures.

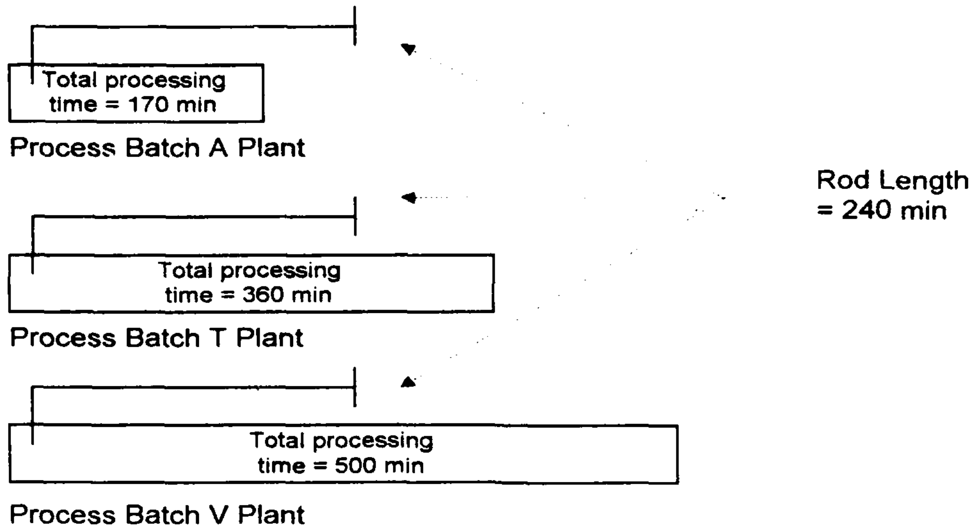


Figure 15: A Comparison of Total Processing Time per Process Batch for Each Plant Type

Analysis of the Difference Between the Best and Worst Schedules

This section responds to Research Objective Five, which is to determine the extent to which *DISASTER*™'s due date performance is affected by different constraint scheduling sequences. Each replication was run through *DISASTER*™ twice, once with the blue bottleneck scheduled first, and once with the gold bottleneck scheduled first. Thus, each replication produced a best and worst schedule in terms of the due date performance objective.

First, the researchers determined whether or not a difference existed. This was accomplished by calculating the percentage of times the best and worst schedules were different for the TDL_{best} and MTD_{best}. In addition, the means and standard deviations were also calculated in order to view the overall magnitude of the difference. Finally, the researchers performed ANOVAs for %DIFFTDL and %DIFFMTD in order to determine the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences at the different levels of the three factors. The percent differences were defined as follows (using TDL as an example):

$$\%\text{DIFFTDL} = \frac{\text{TDL}_{\text{worst}} - \text{TDL}_{\text{best}}}{\text{TDL}_{\text{best}}} \cdot 100\%$$

Descriptive Statistics for the Difference Between Best and Worst Schedules. The data from this research suggests that the constraint scheduling sequence chosen does affect *DISASTER™*'s performance for both TDL and MTD. Of the 108 replications, 99 replications (representing 91.6%) produced different results for TDL when the constraints were scheduled in a different sequence. Of the 108 replications, 71 replications (representing 65.7%) produced different results for MTD.

Table 9 identifies the means and standard deviations for both the best and worst schedules for TDL and MTD, as well as other descriptive statistics. Notice that the means for both TDL_{best} and MTD_{best} were lower than the means for $\text{TDL}_{\text{worst}}$ and $\text{MTD}_{\text{worst}}$ respectively. Therefore, not only are there differences for a large percentage of replications, but the data suggests these differences may be substantial. Further analysis is warranted on %DIFFTDL and %DIFFMTD to determine if there is an impact on the differences in TDL and MTD for *DISASTER™*'s schedules as the levels of the factors change. Once again, the researchers performed ANOVA on %DIFFTDL and %DIFFMTD for this analysis.

Assumptions of ANOVA Addressed. Before the ANOVAs were performed, the researchers had to address the assumptions of this analysis technique. The assumption of independence was met by using the split-plot ANOVA model on the experimental results for %DIFFTDL and %DIFFMTD (Neter et al, 1990:1037). The assumptions of normality and constant variance were evaluated using probability plots, Wilk-Shapiro test statistics, and scatter plots of the residuals. The assumptions were verified for %DIFFTDL and %DIFFMTD. The results of this evaluation can be found in Appendix H.

Table 9

Descriptive Statistics for the Best and Worst Schedules for TDL and MTD

	TDL_{best}	TDL_{worst}	MTD_{best}	MTD_{worst}
Sample Size	108	108	108	108
% Replications Differed	-	91.6%	-	65.7%
Mean (days)	36.6	44.0	7.3	9.1
Standard Deviation (days)	16.1	17.6	2.8	3.5
Minimum (days)	9	10	2	3
Maximum (days)	80	81	16	17
Median (days)	34.5	43.5	7	9

%DIFFTDL. Table 10 is the ANOVA table for %DIFFTDL. At a level of significance of $\alpha = 0.05$, the ANOVA table suggests there are no interactions. The table also suggests there are statistically significant differences in some of the means for the levels of %ΔRCF. Therefore, the researchers performed Tukey's procedure for multiple comparisons for %ΔRCF.

Tukey's Results for %ΔRCF. The Tukey's studentized range test was used to determine which means were statistically different for %ΔRCF. This test suggested that at null %ΔRCF (0%) the mean for %DIFFTDL was significantly different from the mean at low %ΔRCF (25%) at a family level of significance of $\alpha = 0.05$. The test also suggested that neither of the means for the null or the low %ΔRCF were significantly different from the mean at high %ΔRCF. The results of the Tukey's studentized range test can be found in Appendix I.

Table 10

ANOVA Table for %DIFFTDL

ANALYSIS OF VARIANCE TABLE FOR PDTDL

SOURCE	DF	SS	MS	F	P
PLANT	2	11170.9	5585.48	2.16	0.1708
REP					
PLANT*REP	9	23222.0	2580.23		
%RCF	2	256.855	128.427	0.40	0.6785
PLANT*%RCF	4	3244.08	811.021	2.50	0.0788
PLANT*REP*%RCF	18	5832.74	324.041		
%ΔRCF	2	4682.98	2341.49	7.53	0.0042
PLANT*%ΔRCF	4	2559.96	639.991	2.06	0.1288
PLANT*REP*%ΔRCF	18	5594.90	310.827		
%RCF*%ΔRCF	4	926.523	231.630	2.10	0.1010
PLANT*%RCF*%ΔRCF	8	1684.84	210.605	1.91	0.0888
PLANT*REP*%RCF*%ΔRCF	36	3970.76	110.298		
TOTAL	107	63146.7			

Figure 16 displays the means for %DIFFTDL for the three levels of %ΔRCF, as well as the grand mean. Notice the grand mean is 23.1%. In other words, for all 108 benchmark problems, the average percent difference for total days late between the best and worst schedules is 23.1%. Also note that at high %ΔRCF the mean %DIFFTDL decreased from its value at low %ΔRCF. This decrease resulted in a lack of a statistically significant difference between the mean for high %ΔRCF and the means for the other two levels (null and low) for %ΔRCF. Therefore, it is difficult to draw conclusions other than in this experiment, it was more important to identify the primary constraint which produced the best schedule when %ΔRCF was at 25% than when it was at the other two levels.

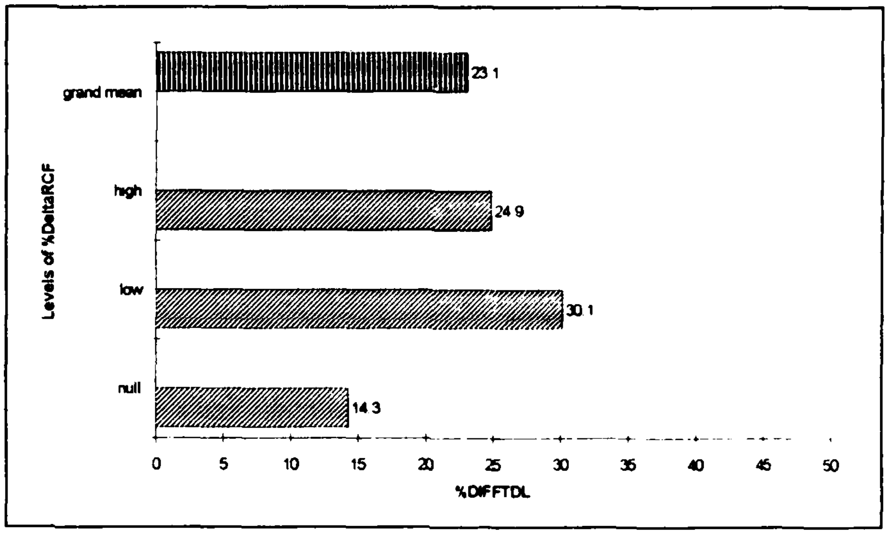


Figure 16: %DIFFTDL versus %RCF

%DIFFMTD. Table 11 is the ANOVA table for %DIFFMTD. At a level of significance of $\alpha = 0.05$, the ANOVA table suggests there are no interactions. The table also suggests there are no statistically significant differences among any of the means for the levels of any of the three factors. In other words, the ANOVA table suggests it is no more or less important to identify the primary constraint which produces the best schedule as the levels of the factors change. However, the constraint sequence chosen does matter for MTD since the grand mean for %DIFFMTD is 27.5% for these benchmark problems.

This section addressed Research Objective Five, which is to determine the extent to which *DISASTER*™'s due date performance is affected by different constraint scheduling sequences. First, the results showed for a large percentage of the 108 replications, the due date performance of the best and worst schedules were different for both TDL and MTD. In addition, the means and standard deviations for TDL_{best}, TDL_{worst}, MTD_{best}, and MTD_{worst} as well as the grand means for %DIFFTDL and

%DIFFMTD suggested a considerable difference between the best and worst schedules for both performance measures. Finally, the ANOVAs for %DIFFTDL and %DIFFMTD suggested there is little impact on the percent difference between the best and worst schedules as the levels of the three factors change.

Table 11

ANOVA Table for %DIFFMTD

ANALYSIS OF VARIANCE TABLE FOR PDMTD

SOURCE	DF	SS	MS	F	P
PLANT	2	24550.4	12275.2	4.05	0.0558
REP					
PLANT*REP	9	27304.2	3033.80		
%RCF	2	1799.30	899.651	3.33	0.0590
PLANT*%RCF	4	1084.69	271.173	1.00	0.4319
PLANT*REP*%RCF	18	4868.76	270.486		
%ΔRCF	2	2484.84	1242.42	0.59	0.5655
PLANT*%ΔRCF	4	845.939	211.484	0.10	0.9810
PLANT*REP*%ΔRCF	18	37997.2	2110.95		
%RCF*%ΔRCF	4	1269.82	317.455	0.98	0.4316
PLANT*%RCF*%ΔRCF	8	932.836	116.604	0.36	0.9350
PLANT*REP*%RCF*%ΔRCF	36	11683.7	324.549		
TOTAL	107	1.148E+05			

Decision Rules for Selecting the Primary Constraint

Since the results of the experiment support the expectation that the sequence in which the constraints are scheduled affects schedule performance, this section considers some decision rules for selecting the primary constraint. Table 12 presents various decision rules, as well as the percentage of times each rule provided the best schedule (or tied for the best) for TDL and MTD.

Table 12

Performance of Decision Rules in This Experiment

Decision Rule for Selecting Primary Constraint	**Number of Replications**	**% of Replications Providing TDL_{best}**	**% of Replications Providing MTD_{best}**
Constraint *DISASTER™* Identified	108	70.4%	97.2%
Constraint *DISASTER™* Identified (%ΔRCF ≠ 0%) [Higher Loaded Constraint]	72	76.4%	100%
Constraint *DISASTER™* Identified (%ΔRCF = 0%)	36	58.3%	91.7%
First Constraint in Operation	72	33.3%	46.7%
Constraint Required for Most Product Types	72	54.2%	73.6%

The table identifies five decision rules. The first decision rule is selecting the primary constraint which *DISASTER™* suggests. The second and third rules are subsets of the first. The second decision rule reflects the fact that when %ΔRCF was not 0%, *DISASTER™* always recommended the higher loaded constraint (gold) as the primary constraint. (Since %ΔRCF was 0% in 36 replications, only 72 of the 108 replications could be used for the analysis of this decision rule.) The second decision rule reflects *DISASTER™*'s recommendation (rationale unknown to the researchers) in the 36 replications where %ΔRCF was 0%. The fourth decision rule is selecting the bottleneck resource with the first constraint process station in the operation as the primary constraint. This rule was considered since this is the first constraint that is encountered in the production flow. Therefore, a scheduler may want to schedule this constraint first. (Again, 36 of the 108 replications could not be included since both the blue and the gold resources had process stations an equal distance into the operation in the T plant replications.) The final decision rule shown is selecting the resource that is required in the production of the most product types. This rule was selected since it has the potential to affect the most job orders. (This time 36 of the 108 replications could not be included since both the blue and the gold resource were required to produce the single product type in the A plant replications.)

Overall, *DISASTER™* recommended the primary constraint that provided the best (or one that tied for the best) schedule for 97.2% of the replications for MTD. However, when TDL was the due date performance measure, *DISASTER™*'s recommendation was best in 70.4% of the replications. This data suggests that *DISASTER™*'s recommendation for primary constraint provides the best schedule more often when MTD is the due date performance measure than when TDL is the due date performance measure.

When %ΔRCF was not 0%, *DISASTER™* always chose the heavier loaded constraint (gold resource) as the primary constraint. *DISASTER™*'s reliance on the higher loaded constraint is consistent with Goldratt's book, *The Haystack Syndrome*. According to Goldratt, after subordination to the market, if constraints are identified "from all the resources that do not have sufficient capacity, only the resource that lacks capacity the most can at this stage be declared as a suspected resource constraint" (Goldratt 1990:195). In other words, Goldratt seems to imply that the heaviest loaded constraint should always be scheduled first. This decision logic resulted in *DISASTER™* choosing the primary constraint that gave the best schedule for 100% of the replications for MTD. On the other hand, for TDL when %ΔRCF was not 0%, *DISASTER™*'s choice of the higher loaded was best in only 76.4% of the replications.

When %ΔRCF was 0%, *DISASTER™*'s recommendation for the primary constraint did not provide the best schedule as often as when %ΔRCF was not 0%. However, *DISASTER™*'s choice for the primary constraint still provided the best schedule for a substantial percentage (91.7%) of the replications when MTD was the due date performance measure. When TDL was the due date performance measure and %ΔRCF was 0%, *DISASTER™*'s choice for the primary constraint provided the best schedule for 58.3% of the replications. This is a substantial decrease in percentage from when %ΔRCF was not 0% for TDL, but is still better than the two remaining rules in the table.

The final two decision rules for selecting the primary constraint, choosing the first constraint in the operation and choosing the constraint required for the most product types, did not perform nearly as well as *DISASTER™*'s recommendation. Although both rules reflect logic which is likely to appeal to schedulers in practice, the data from this experiment suggests using *DISASTER™*'s recommendation over either of these two decision rules for both TDL and MTD.

After completing this experiment, the researchers highly recommend running both constraint scheduling sequences through *DISASTER™*. The data suggests this is especially true when minimizing TDL is the desired due date performance objective. The amount of time it takes to rerun *DISASTER™* is insignificant (approximately 10 minutes) when compared to the amount of improvement possible in the schedule.

Nuances Involved With Using DISASTER™

The researchers found three important, undocumented nuances in the *DISASTER™* software. These nuances, if not acknowledged, could result in misleading schedules, or at least schedules based on principles of which the user may not be aware. Two of these nuances had to do with *DISASTER™* calculating the revised completion dates for late job orders. The third nuance concerns transfer batches (batches of parts passed from one processing station to the next).

First Nuance. The researchers discovered that when processing for some job orders continued past the end of the time horizon (two weeks for these benchmark problems), *DISASTER*™'s job order completion dates were different than when the time horizon was lengthened to include all processing required to produce all job orders. In other words, if processing was required past the end of the time horizon, *DISASTER*™ did not produce the entire schedule for all job orders. It only provided a schedule for the processing required within the time horizon. This schedule did not include the remainder of the processing required after the time horizon. However, *DISASTER*™ did provide completion dates for all job orders, even if the entire schedule was not produced. This situation occurred most often in the heavily loaded replications (replications with large %RCFs and %ΔRCFs) since these replications required a greater amount of processing after the end of the time horizon.

The researchers investigated actions required to obtain the entire schedule for all processing required to produce all job orders. They found that lengthening the time horizon input to *DISASTER*™ produced the entire schedule for all required processing. The following steps identify the way the researchers worked around this nuance. First, run the SCHEDULE module only through the **IDENTIFICATION SCREEN** with the original time horizon. This process allows the user to see how the resources of the plant are loaded during the horizon of interest. Second, return to the **PARAMETER SCREEN** and change the time horizon's End Date to a date far in the future (a date far enough in the future so that it will not be possible for processing to continue past the end of the time horizon given the number of job orders being scheduled). Third, finish running the SCHEDULE module with the new End Date. After this process is complete, the user will have an entire schedule for all job orders.

When this work-around was accomplished, the researchers discovered some of the completion dates were different with the lengthened time horizon than when the time horizon was equal to the original two weeks. Specifically, when the time horizon was two weeks, the completion dates for all job orders were the same or earlier than the completion dates when the time horizon had been lengthened. This was surprising since the researchers assumed the completion dates would be the same whether or not the entire schedule was provided by *DISASTER™*. Since the entire schedule is not produced when processing is required past the end of the time horizon, the researchers assumed the reported completion dates were only estimates. The heuristic used to estimate these completion dates is not provided in any of the *DISASTER™* documentation. In addition, the researchers were unable to uncover the logic *DISASTER™* used in estimating these completion dates during the experiment. Since the entire schedule is produced with the lengthened time horizon, the researchers knew exactly how the completion dates were arrived at and were confident these dates could be achieved. Therefore it was these completion dates that were utilized throughout the experiment.

Second Nuance. The second nuance the researchers found when working with *DISASTER™* is a subtly documented heuristic for deciding if a job order is late, and if it is late, how the revised completion date is calculated. The heuristic can be summarized in the following if-then-else statement.

IF - The last constraint process station of a job order is finished earlier than the due date minus one half of a shipping buffer

THEN - The job order is on time, and the date reported is the date of the original due date (even if processing is finished extremely early)

ELSE - If the job order is finished processing on the last constraint process station later than due date minus one half of a shipping buffer; then add a shipping buffer to the end time of the process batch and report the job order as late and the resultant completion date is this sum.

The result of this heuristic is that *DISASTER™* does not allow any tardiness to be less than or equal to one half of a shipping buffer. Thus, if one job order is finished processing one minute earlier than the due date minus one half a shipping buffer, it is considered to be on time and its completion date will be reported as the original due date. If another job order is finished one minute later than the due date minus one half a shipping buffer, it is late and its revised completion date is the sum of this finish time and a shipping buffer.

Figure 17, Figure 18, and Figure 19 identify examples which apply this heuristic. Figure 17 identifies the final constraint process batch for a job order scheduled to be completed at its ideal finish time. The ideal finish time is the job order's due date minus one shipping buffer. In this case, the completion date reported by *DISASTER™* is the same date as the original due date.

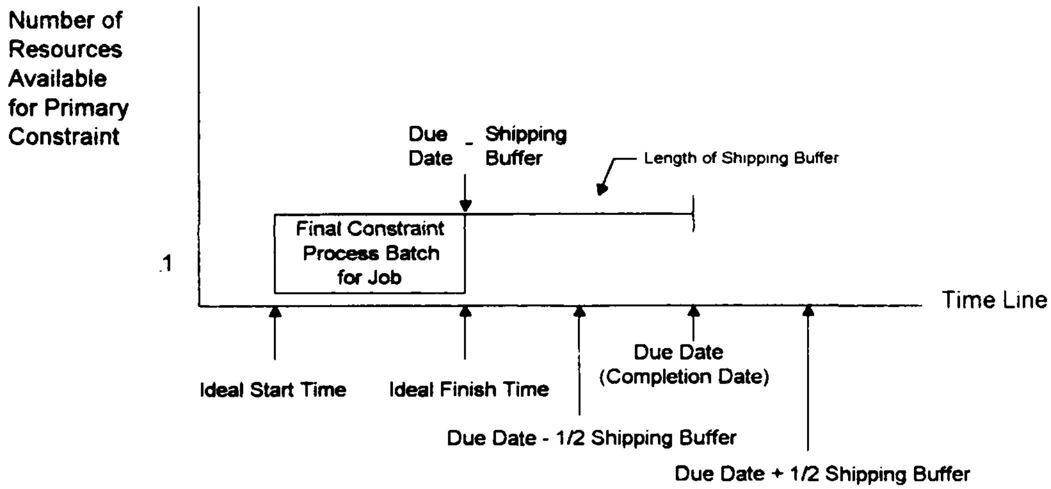


Figure 17: Revised Completion Date Heuristic Example 1

Figure 18 identifies the process batch which is scheduled to be completed between its ideal finish time (due date minus one shipping buffer) and due date minus one half of a shipping buffer. In this case, the completion date reported by *DISASTER™* is still the original due date.

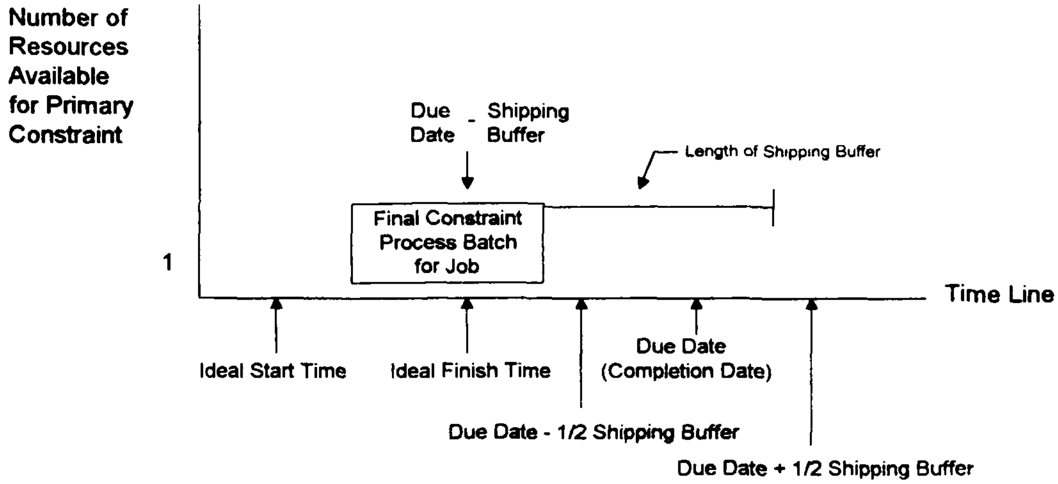


Figure 18: Revised Completion Date Heuristic Example 2

Figure 19 identifies the process batch scheduled to be completed after the due date minus one half of a shipping buffer. In this case, the completion date reported by *DISASTER™* is the scheduled completion time of this process batch plus one shipping buffer. Based upon this heuristic, if *DISASTER™* reports a job order as being late, it will always be reported as at least one half of a shipping buffer late.

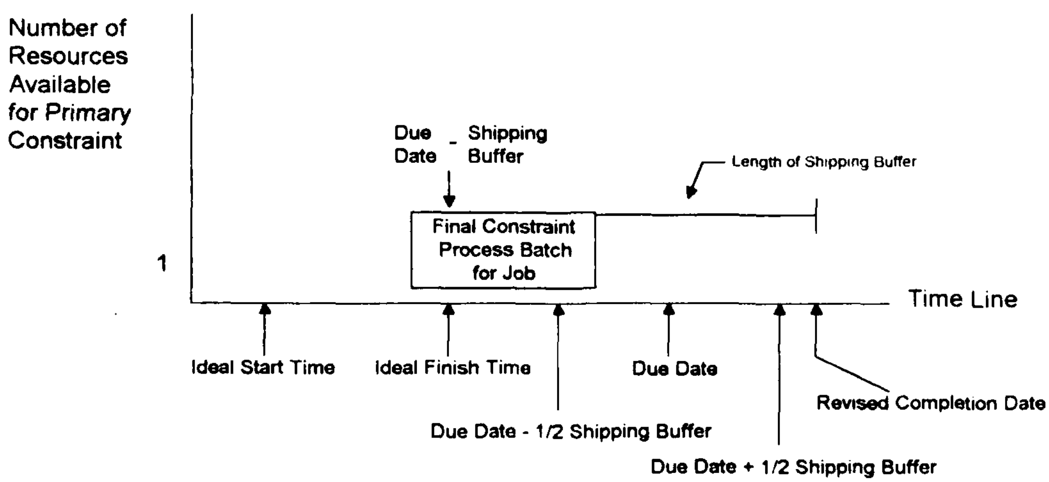


Figure 19: Revised Completion Date Heuristic Example 3

Third Nuance. Although not documented in the manual, the researchers found on the **DISPLAY RODS SCREEN** that *DISASTER*™ allows for overlaps in process batches. This means a bottleneck process station can begin working on the parts completed by the previous bottleneck process station before the previous bottleneck station has completed the entire process batch. This overlapping of process batches (requiring the use of smaller transfer batches) shortens the makespan of *DISASTER*™'s schedule for a set of job orders.

Figure 20 identifies an example of why smaller transfer batches are required. This example has a gold constraint process station feeding a blue constraint process station with a single interim non-constraint process station. Note the constraint process batches overlap. The only way it is possible to begin processing on the blue resource at its scheduled time is by transferring some fraction of the units processed by the gold resource before the entire batch is completed. Notice from Figure 20 that the maximum number of units in the transfer batch is the number of units which can be processed before the scheduled start time of the non-constraint process station.

While widely espoused as an assumed capability in a DBR system, the use of transfer batches is not explicitly stated in *DISASTER*™'s documentation, nor is the size of the required transfer batches reported in the output files. Therefore a user of *DISASTER*™ must analyze the **DISPLAY RODS SCREEN** in conjunction with the output files to determine the maximum size of the transfer batches.

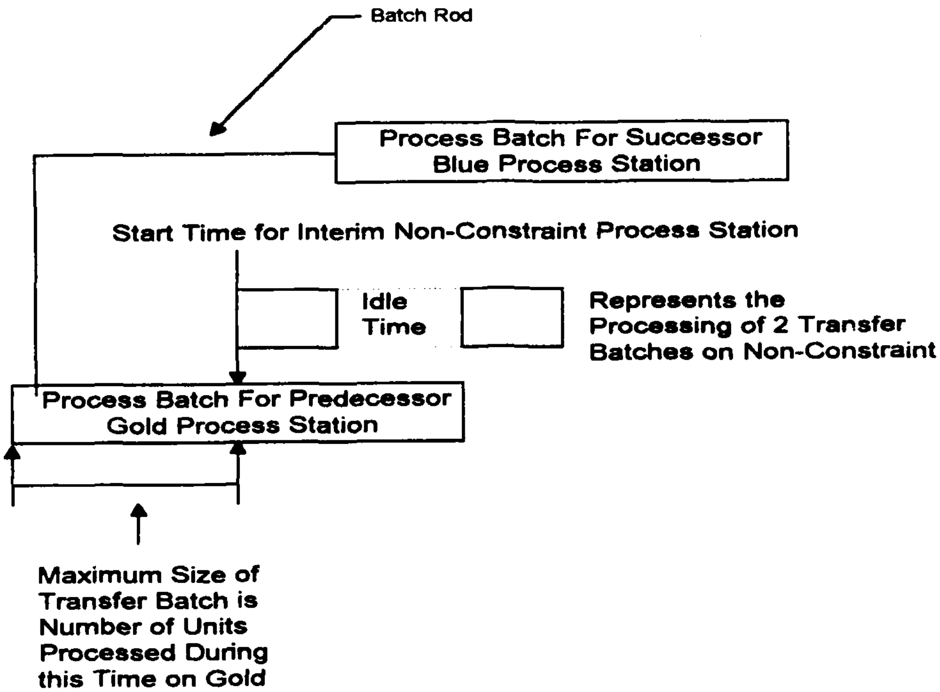


Figure 20: Transfer Batch Example

Summary

The purpose of this chapter was to discuss this study's findings and the relevance of these findings. First, the accomplishment of the experiment was described. Second, the actual results of the experiment were presented along with a discussion of the significance of the results. Third, alternative decision rules for choosing primary constraints were compared. Finally, some of the nuances the researchers discovered while using *DISASTER*™ were discussed. The next chapter summarizes this thesis, highlights its contributions, and suggests future research opportunities.

V. Conclusions

The purpose of this chapter is to summarize this research effort. First, the purpose of this thesis and its five research objectives are reiterated. In addition, this section includes the significance of the findings of this research. Second, some topics that require future research are presented.

Significance of this Research

DISASTER™ has the capability to schedule a manufacturing environment with interactive constraints; however, *DISASTER™* can produce alternative schedules which may not be identical. *DISASTER™* does not simultaneously schedule interactive constraints, but rather sequentially schedules each constraint (Newbold, 1992; Newbold Atch, 1990:1). The schedules produced are dependent on the constraint sequence chosen by the scheduler.

This research effort addressed this specific problem in two ways. First, the researchers developed a set of benchmark problems of job shops with interactive constraints to produce a diversity of scheduling scenarios. Second, the researchers determined the relationship between the quality of *DISASTER™*'s schedules and the constraint sequence chosen for these benchmark problems.

Five research objectives were addressed. Each research objective addressed one aspect of the overall problem. Thus, a review of the objectives effectively summarizes this research effort.

Research Objective 1: to define the *DISASTER™* scheduling logic in algorithmic form

The algorithmic form of *DISASTER™*'s logic can be found in Appendix A. The algorithm covers subordination of the job hop's resources to the market, the identification and exploitation of a primary resource constraint, the subordination of all other resources to this constraint, the identification and exploitation of a secondary resource constraint, and the drum violation and drum loop to fix the violation.

There are many references which discuss DBR scheduling as well as the basic logic used by *DISASTER™*. These sources include *The Haystack Syndrome*, *The Race*, and the *DISASTER™* documentation. However, to the researchers' knowledge, the *DISASTER™* algorithm is not completely documented in any published literature. Thus, this thesis provides a reference for future researchers, as well as users of *DISASTER™*, wishing to gain insight into its algorithm.

> Research Objective 2: to develop a set of benchmark problems that represent a diversity of scheduling scenarios with respect to the capabilities of the *DISASTER™* algorithm

The researchers attempted to choose experimental factors that would cause changes in the performance of the schedules created by *DISASTER™* as the levels of the experimental factors changed. The experimental factors the researchers chose were plant type, %RCF, and %ΔRCF. Plant type was chosen since it is documented in the relevant literature as a way to characterize significantly different job shops (Newbold, 1992; Fawcett and Pearson, 1991). Thus, the researchers felt it would be important to evaluate *DISASTER™*'s behavior in all three different plant types. However, the use of a split-plot ANOVA precludes the ability to statistically support significant differences in *DISASTER™*'s due date performance across the different plant types. (Plant type was a completely confounded variable.)

The other two factors, %RCF and %ΔRCF, were chosen because this study focused on the exploitation of two bottleneck resources (the scheduling of the two drums). The researchers felt variables which defined the level of demand for each bottleneck would make excellent experimental factors. The researchers anticipated that

DISASTER™'s performance is a function of the load on the constraints. The %RCF factor identifies the workload relative to capacity in a given time period. The %ΔRCF factor identifies the percent difference between the %RCF loading between the bottlenecks in a job shop with two interactive constraints. The results showed that both of these factors also caused significant differences in *DISASTER™*'s results. Therefore these two factors helped to create diversity in the scheduling scenarios for the benchmark problems.

In addition to the three factors described above, the researchers defined and addressed background variables that could possibly skew the results. According to Moen, Nolan, and Provost, background variables must either be controlled or used to establish a wide range of range of conditions (Moen et al, 1991:70). This experiment had 16 background variables. For all background variables except two, the variables were controlled by holding them constant throughout the experiment. The two exceptions were job order due dates and product types/location of constraint process station. These background variables were varied in order to establish a wide range of conditions for the experiment.

These benchmark problems can be used in future studies to evaluate other scheduling algorithms. In addition, these benchmark problems allow future researchers the capability to analyze the impact different independent variables may have on *DISASTER™*'s performance (or some other scheduling algorithm's performance).

Research Objective 3: to produce solutions (schedules) for the benchmark problems using the *DISASTER™* software

In order to meet this objective, the researchers ran each of the 108 replications through *DISASTER™* twice: once with the gold (higher loaded) constraint scheduled first, and once with the blue (lower loaded) constraint scheduled first. The researchers gained insights into *DISASTER™*'s logic and found nuances involved with using *DISASTER™* while meeting this objective. These insights and nuances can be found in Chapter IV.

Research Objective 4: to evaluate *DISASTER™*'s due date performance as the levels of the factors change to ensure the benchmark problems produce a diversity of scheduling scenarios

As stated from Research Objective 2, the experimental results suggest %RCF and %ΔRCF caused a diversity of scheduling scenarios for the benchmark problems. *DISASTER™* showed a wide diversity of performance across the factors for both due date performance objectives: total days late and maximum tardiness. By obtaining a diversity of scheduling scenarios, the problems can be used as a good benchmark to compare the performance of other scheduling algorithms to the performance of *DISASTER™*.

Research Objective 5: to determine the extent to which *DISASTER™*'s due date performance is affected by different constraint scheduling sequences

The results suggest that the sequence in which the constraints are scheduled affects the performance of the schedules produced by *DISASTER™*. Users of *DISASTER™* should be aware that if interactive constraints are identified, and only one constraint sequence is chosen, the resultant schedule may not be the best *DISASTER™* can provide. *The Haystack Syndrome* implies that it is always best to schedule the heaviest loaded constraint first (Goldratt, 1990:195). However, when total days late was the due date performance objective, this study showed scheduling the heaviest loaded constraint first does not always provide the best *DISASTER™* schedule.

The researchers suggest if interactive constraints are identified, the user produces *DISASTER™* schedules for all possible constraint sequences. The experience of the researchers suggests that the amount of time it takes to rerun *DISASTER™* is small and well worth the possible improvement in schedule performance.

Future Research

Very little research has been done on the *DISASTER™* scheduling software package or the problem of scheduling interactive constraints. This research effort has only scratched the surface of understanding all the implications the implementation of *DISASTER™* has on a production operation. Future research in this area is important to the Air Force since depots are exploring the implementation of *DISASTER™* to schedule their operations. The following areas need to be researched if Air Force depots are to maximize the benefits of implementing *DISASTER™*:

1) In this experiment, all buffer sizes were held constant. This resulted in constant rod lengths throughout the experiment. However, total processing time for process batches varied among the different plant types. Resource constraint buffer size (which determines rod length) may impact the performance of *DISASTER™* across plant types. Future research should evaluate resource constraint buffer size as an experimental factor. While varying resource constraint buffer size as the independent variable, total processing time for process batches should be held constant. Figure 21 identifies the situation where rod length is varied while total processing time for the process batches is held constant. Note the length of the rod may or may not extend past the finish time of the process batch. The end time of this rod determines when the successor constraint process station can be scheduled to begin. Future research would provide insight to a depot manager about the effect buffer size (and thus rod length) has on *DISASTER™*'s due date performance.

2) Other due date performance measures should be analyzed in an experiment similar to the one conducted in this thesis. The researchers suggest total number of late job orders. This performance measure is important to the Air Force. When an operational squadron is deploying, repaired aircraft parts must be available at the time of deployment. The magnitude of tardiness is not of paramount importance in this situation, since one day

late may be as undesirable as ten days late. The goal here is to minimize the total number of tardy repairs.

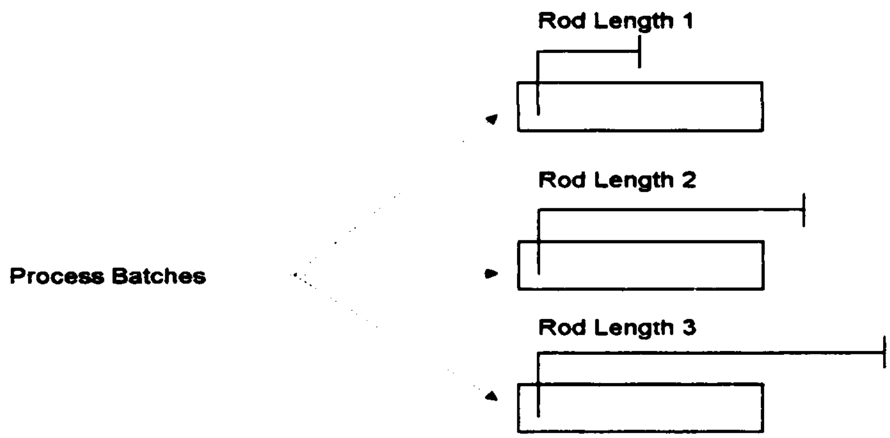


Figure 21: Variation in Rod Length With Constant Total Processing Time for Process Batches

3) A survey of Air Force depots is warranted in order to ascertain the prevalence of interactive constraints in these manufacturing environments. If depots contain only one constraint resource in their operation, the line of research in this thesis (studying the effect of interactive constraints) is unnecessary for the USAF. Conversely, if some depots contain two or more constraint resources, the line of research in this thesis must be continued and expanded.

4) In this experiment, plant type was the completely confounded variable for the split-plot factorial design. This limited the analysis across the levels for plant type (A plant, T plant, V plant). The researchers believe this factor may have significant impact on *DISASTER™*'s due date performance. If the split-plot experimental design was slightly modified by randomly sampling job order due dates at every treatment level, plant type would no longer be a completely confounded variable. The resulting experimental design

would be a full factorial experimental design. However, the sample size (number of replications) for each treatment must be increased since the split-plot experimental design would no longer be employed.

VI. Glossary

Assembly Buffer: A stock of WIP produced only by non-constraint resources which is placed before an assembly process station which is also fed by parts which were processed by a constraint(s)

Available Capacity: Maximum usable production or output of a resource in a given amount of time.

Bottleneck: A resource which has more demand placed on it than it has **available** capacity.

Buffer: Work-in-process inventory strategically placed in an operation to protect the throughput against any disruptions. A buffer is expressed in terms of time.

Capacity: Potential production or output of a resource in a given amount of time.

Capacity Constraint Resource: A type of constraint resource which has more demand placed on it than it has **protective** capacity.

Constraint: Anything that limits throughput. A resource which has more demand placed on it than it has capacity (either available or protective).

Constraint Resource: See **Constraint**

Constraint Exploitation: The process of ensuring that a constraint is not scheduled to produce more than it has capacity and not to waste any of the constraint's capacity by allowing any slack in its schedule.

Demand: Requirement for production or output of a resource.

Drum: The schedule produced for a constraint resource.

Drum-Buffer-Rope (DBR): The scheduling technique which applies the principles of the Theory of Constraints. (See definitions for drum, buffer, and rope)

Effective Horizon: Length of time used to account for job orders that may have due dates just after the end of the time horizon, but for which processing may be required inside the time horizon. The length of the effective horizon is defined as the time horizon plus one shipping buffer.

Interactive Constraint: A constraint which feeds, or is fed by, another constraint process station.

Job Order: The quantity of a product type wanted at a specified time.

Non-Constraint Resource: A resource that is not identified as limiting the throughput of the operation.

Operation: All process stations required to produce all product types.

Primary Constraint: A constraint which, when first identified, **does not** interact with another constraint.

Process Batch: A certain number of parts (batch) which is processed by a resource before a setup is performed for the resource to run another batch for a different process station.

Process Station: A particular resource, setup in a particular manner, to perform work in a particular place in the production sequence of a product type.

Processing Time: The time required to produce one unit for a given process station.

Product Type: A finished good produced using certain process stations in a particular sequence.

Protective Capacity: The unscheduled portion of available capacity on a non-constraint resource which enables it to catch up after a breakdown or other mishap.

Resource: A certain type of machine or labor.

Resource Constraint: See **Constraint**

Resource Constraint Buffer: Stock of WIP placed before a resource constraint to protect the throughput of the resource constraint by assuring it is never idle due to disruptions upstream in the operation.

Rope: Timed release of raw materials into the operation in order to limit the amount of work-in-process inventory.

Shipping Buffer: A stock of finished goods of a product type which protects the integrity of promised due dates for the product.

Secondary Constraint: A constraint which when first identified **does** interact with another constraint.

Setup Time: The time required to modify a resource to perform work as a different process station.

Time Horizon: Length of time for which resources are to be scheduled.

Theory of Constraints (TOC): A management theory developed by Eliyahu Goldratt and based on the belief that an operation should be managed by controlling its constraints.

Transfer Batch: A certain number of parts (batch) which must be produced before being physically moved from one process station to another.

Appendix A: DISASTER™ Logic in Algorithmic Form

STEP 1: SUBORDINATE RESOURCES TO MARKET (DUE DATES)

```
Identify market (due dates) as constraint
Calculate all process batches to fill job orders
    DO  for all job orders, from earliest due date to latest due date
        DO  for each process station in job order from last to first
            process batch = (processing time)(# units in job order)
        ENDDO
    ENDDO
Allocate WIP to process batches
    DO  for all job orders, from earliest due date to latest due date
        DO  for each process station in job order from last to first
            IF
            WIP completed by process station = 0
                THEN
                process batch is unchanged
            ELSE
            process batch = (processing time)(# units in job order - WIP)
            # units in job order = # units in job order - WIP
            ENDIF
        ENDDO
    ENDDO
Schedule job orders
    DO  for each day from last scheduling day to first scheduling day
        DO  for all job orders, from latest due date to earliest due date
            DO  for each process station in job order (with a calculated process
            batch) from last to first
                IF
                process station is last in operation for job order
                    THEN
                    finish time = due date - shipping buffer
                ELSE
                finish time = start time of successor process station
                ENDIF
                start time = finish time - process batch - setup time
                IF
                workday is day 1
                start time is before day 1
                    THEN
                    daily resource load = daily resource load + (finish
                        time - start time)
                ELSEIF
                start time is in this workday
```

```
                THEN
                daily resource load = daily resource load + (finish
                    time - start time)
            ELSE
            daily resource load = daily resource load + finish time
            daily resource load for previous day = total workhrs in day -
                start time
            ENDIF
            IF
            process station is first
                THEN
                raw material release = start time
            ENDIF
        ENDDO
    ENDDO
ENDDO
```

Identify First Day Load (FDL) peak

```
DO  for each resource type
    IF
    daily resource load day 1 > daily resource worktime day 1 + (1/2)(resource
        constraint buffer)
        THEN
        highlight resource with FDL peak
    ENDIF
ENDDO
IF
# FDL peaks = 0
    THEN
    use schedule and END
ELSE
go to STEP 2
ENDIF
```

STEP 2: IDENTIFY AND EXPLOIT RESOURCE CONSTRAINT

Choose a resource with FDL peak as drum

Create Ruins schedule

```
DO  for each job order requiring a drum process station (with calculated process
batch), from earliest due date to latest due date
    DO  for each drum process station (with calculated process batch), from
    last to first
```

```
                        IF
                        process station is last drum process station (with calculated process
                                batch) for job order
                                THEN
                                finish time = due date - shipping buffer
                                start time = finish time - process batch - setup time
                        ELSEIF
                        processing time > processing time successor drum process station
                                THEN
                                finish time = finish time successor - processing time
                                        successor - (1/2)(resource constraint buffer)
                                start time = finish time - process batch - setup time
                        ELSE
                        start time = (start time successor + setup time successor) -
                                (1/2)(resource constraint buffer) - (setup time + processing
                                time)
                        finish time = start time + setup time + process batch
                        ENDIF
                ENDDO
        ENDDO
```

Create backwards pass schedule

```
        DO for each drum process station (with calculated process batch), from latest
        finish time to earliest finish time
                IF
                no drum process stations have been scheduled
                        THEN
                        finish time = finish time
                        start time = start time
                ELSEIF
                finish time < start time of last scheduled drum process station
                        THEN
                        finish time = finish time and start time = start time
                ELSE
                finish time = start time of last scheduled drum process station
                start time = finish time - process batch - setup time
                ENDIF
        ENDDO
```

Create forward pass schedule

```
        IF
        no drum process stations have a start time < time 0:00, day 1
                THEN
                go to STEP 3
        ENDIF
```

```
DO  for each drum process station (with calculated process batch), from earliest
start time to latest start time
        IF
        no drum process stations have yet been scheduled
                THEN
                start time = time 0:00, day 1
                finish time = start time + setup time + process batch
        ELSEIF
        start time < finish time of last scheduled drum process station
                THEN
                start time = finish time of last scheduled drum process station
                finish time = start time + setup time + process batch
        ENDIF
        IF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor > processing time successor
                THEN
                ready time = finish time predecessor + (1/2)(resource constraint
                        buffer) + processing time successor - process batch
                        successor - setup time successor
        ELSEIF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor < processing time successor
                THEN
                ready time = start time predecessor + setup time + processing time
                        predecessor + (1/2)(resource  constraint buffer) - setup time
                        successor
        ENDIF
        IF
        start time < ready time
                THEN
                start time = ready time
                finish time = start time + setup time + process batch
        ENDIF
ENDDO
go to STEP 3
```

STEP 3: SUBORDINATE ALL OTHER RESOURCES TO DRUM

Schedule non-constraint process stations

```
DO  for each day from last scheduling day to first scheduling day
        DO  for all job orders, from latest due date to earliest due date
```

```
                    DO  for each non-constraint process stations in job order (with a
                    calculated process batch) from last to first
                        IF
                        process station is last
                            THEN
                            finish time = due date
                        ELSE
                        finish time = start time of successor process station
                        ENDIF
                        start time = finish time - process batch - setup time
                        IF
                        workday is day 1
                        start time is before day 1
                            THEN
                            daily resource load = daily resource load + (finish
                                time - start time)
                        ELSEIF
                        start time < predecessor constraint process station start time
                            + setup time + processing time
                            THEN
                            highlight Red Lane Peak (RLP)
                            go to STEP 4
                        ENDIF
                        IF
                        start time is in this workday
                            THEN
                            daily resource load = daily resource load + (finish
                                time - start time)
                        ELSE
                        daily resource load = daily resource load + finish time
                        daily resource load for previous day = total workhrs in day -
                            start time
                        ENDIF
                        IF
                        process station is first
                            THEN
                            raw material release = start time
                        ENDIF
                    ENDDO
                ENDDO
            ENDDO
```

Identify First Day Load (FDL) peak

```
            DO  for each resource type
```

```
        IF
        daily resource load day 1 > daily resource worktime day 1 + (1/2)(resource
                constraint buffer)
                THEN
                highlight resource with FDL peak
        ENDIF
ENDDO
IF
# FDL peaks = 0
        THEN
        use schedule and END
ELSE
go to STEP 4
ENDIF
```

STEP 4: IDENTIFY AND EXPLOIT SECONDARY RESOURCE CONSTRAINT

Choose resource with FDL peak or RLP as drum
Create Ruins schedule

```
DO  for each job order requiring drum process station (with calculated process
batch), from earliest due date to latest due date
        DO  for each secondary drum process station (with calculated process
        batch), from last to first
                IF
                process station is last drum process station (with calculated process
                batch) for job order
                        THEN
                        finish time = due date - shipping buffer
                        start time = finish time - process batch - setup time
                ELSEIF
                processing time > processing time successor drum process station
                        THEN
                        finish time = finish time successor - processing time
                                successor - (1/2)(resource constraint buffer)
                        start time = finish time - process batch - setup time
                ELSE
                start time = (start time successor + setup time successor) -
                        (1/2)(resource constraint buffer) - (setup time + processing
                        time)
                finish time = start time + setup time + process batch
                ENDIF
        ENDDO
ENDDO
```

Create backwards pass schedule

```
    DO  for each secondary drum process station (with calculated process batch), from
    latest finish time to earliest finish time
        IF
        no secondary drum process stations have been scheduled
            THEN
            finish time = finish time
            start time = start time
        ELSEIF
        finish time < start time of last scheduled drum process station
                THEN
                finish time = finish time
                start time = start time
        ELSE
        finish time = start time of last scheduled drum process station
        start time = finish time - process batch - setup time
        ENDIF
    ENDDO
```

Create forward pass schedule

```
    IF
    no secondary drum process stations have a start time < time 0:00, day 1
        THEN
        DO  for each secondary drum process station (with calculated process
            batch), from latest finish time to earliest finish time
        IF
        start time < ready time of successor initial drum process station
            THEN
            highlight as drum violation
            drum violation = ready time - start time
            go to STEP 5
        ENDIF
        ENDDO
        go to STEP 3
    ENDIF
    DO  for each secondary drum process station (with calculated process batch), from
    earliest start time to latest start time
        IF
        no drum process stations have yet been scheduled
            THEN
            start time = time 0:00, day 1
            finish time = start time + setup time + process batch
        ELSEIF
        start time < finish time of last scheduled drum process station
```

```
            THEN
            start time = finish time of last scheduled drum process station
            finish time = start time + setup time + process batch
        ENDIF
        IF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor > processing time successor
            THEN
            ready time = finish time predecessor + (1/2)(resource constraint
                buffer) + processing time successor - process batch
                successor - setup time successor
        ELSEIF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor < processing time successor
            THEN
            ready time = start time predecessor + setup time + processing time
                predecessor + (1/2)(resource  constraint buffer) - setup time
                successor
        ENDIF
        IF
        start time < ready time
            THEN
            start time = ready time
            finish time = start time + setup time + process batch
        ENDIF
    ENDDO
    DO  for each secondary drum process station (with calculated process batch), from
    latest finish time to earliest finish time
        IF
        start time < ready time of a successor initial drum process station
            THEN
            highlight as drum violation
            drum violation = ready time - start time
            go to STEP 5
        ENDIF
    ENDDO
    go to STEP 3
```

STEP 5: DRUM LOOP TO FIX VIOLATION

Fix violation with initial drum schedule

```
    DO  for each initial drum process station scheduled, from process station with
    violation to last process station
```

```
        IF
        process station is process station with drum violation
                THEN
                start time = start time + drum violation
                end time = end time + drum violation
        ELSEIF
        start time < finish time of last scheduled drum process station
                THEN
                start time = finish time of last scheduled drum process station
                finish time = start time + setup time + process batch
        ENDIF
        IF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor > processing time successor
                THEN
                ready time = finish time predecessor + (1/2)(resource constraint
                        buffer) + processing time successor - process batch
                        successor - setup time successor
        ELSEIF
        drum process station has a predecessor drum process station scheduled
        processing time predecessor < processing time successor
                THEN
                ready time = start time predecessor + setup time + processing time
                        predecessor + (1/2)(resource constraint buffer) - setup time
                        successor
        ENDIF
        IF
        start time < ready time
                THEN
                start time = ready time
                finish time = start time + setup time + process batch
        ENDIF
ENDDO
go to STEP 3
```

Appendix B: Due Date Assignment Data

General Notes

1) Number of Process Stations: Each plant type contained 30 total process stations. Most product types require less than the total number of process stations. The only exception is the single product produced by the A plant. (For graphical displays of the plant networks see Appendix B.) The due date assignment rule used in this thesis assigned due dates based on the number of process stations for the job order's product type. The number of process stations for each job order is listed next to each product type in the tables.

2) Calculation of the Constants: Arrival dates from the previous two weeks (20 Sep 93 to 1 Oct 93) were randomly sampled with replacement for the 40 job orders for each plant type (4 replications x 10 job orders = 40 total job orders). In order to calculate the constant used to assign due dates, the job order (from the 40 per plant type) whose product type had the greatest number of process stations as well as the latest arrival date was selected. The researchers assigned the last day *of the time horizon* (15 Oct 93) as the due date for this job order. Since the due date, arrival date, and number of process stations are known for this job order, the constant for this plant type can be calculated using the following equations:

$$\text{Flow Time} = \text{Due Date} - \text{Arrival Date}$$

$$\text{Constant} = \frac{\text{Flow Time}}{\text{\# Process Stations}}$$

This constant was then applied to the remaining job orders for the particular plant type to calculate the due dates. This ensured none of the other job orders would have a due date past the end of the time horizon for this plant type. This process was accomplished to calculate due date assignment constants for all three plant types.

3) Calculated Due Dates (Initial versus Final): Occasionally, after applying the above equations, a job order's due date fell before day one of the time horizon (4 Oct 93).

For the few situations in which this occurred, these initial due dates were used as new arrival dates and the above equations were reapplied to calculate final due dates for these job orders which fell within the time horizon. When this situation did not occur, the initial due date was not applicable (N/A) and the calculated due date was simply the final due date.

In addition, occasionally **none** of the ten job orders in a replication fell on the final day of the experimental time horizon (15 Oct 93). When this occurred, the job order with the latest calculated due date was assigned a new due date; this new due date was 15 Oct 93. This action was necessary because a constant time horizon for all replications in the experiment was required. A constant time horizon was required because both *DISASTER™* and %RCF determine resource loading based upon the length of the time horizon (which is defined by the due date of the latest job order). If the time horizon varied among replications, the resource loading reported by *DISASTER™* and the %RCF would have varied among replications. This situation would not have allowed analysis across levels for %RCF.

A Plant Due Dates

Plant Type / Replication #	Job Order #	Product Type / # Process Stations (Sampled Without Relacement)	Arrival Date (Sampled With Replacement)	Constant (days/station)	Calculated Due Date (Initial)	Calculated Due Date (Final)
A - Plant / Rep 1	1	D - FG / 30 stations	22-Sep-93	0.33	N/A	6-Oct-93
A - Plant / Rep 1	2	D - FG / 30 stations	1-Oct-93	0.33	N/A	15-Oct-93
A - Plant / Rep 1	3	D - FG / 30 stations	27-Sep-93	0.33	N/A	11-Oct-93
A - Plant / Rep 1	4	D - FG / 30 stations	20-Sep-93	0.33	N/A	4-Oct-93
A - Plant / Rep 1	5	D - FG / 30 stations	30-Sep-93	0.33	N/A	14-Oct-93
A - Plant / Rep 1	6	D - FG / 30 stations	21-Sep-93	0.33	N/A	5-Oct-93
A - Plant / Rep 1	7	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 1	8	D - FG / 30 stations	29-Sep-93	0.33	N/A	13-Oct-93
A - Plant / Rep 1	9	D - FG / 30 stations	21-Sep-93	0.33	N/A	5-Oct-93
A - Plant / Rep 1	10	D - FG / 30 stations	29-Sep-93	0.33	N/A	13-Oct-93
A - Plant / Rep 2	1	D - FG / 30 stations	30-Sep-93	0.33	N/A	14-Oct-93
A - Plant / Rep 2	2	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 2	3	D - FG / 30 stations	29-Sep-93	0.33	N/A	13-Oct-93
A - Plant / Rep 2	4	D - FG / 30 stations	1-Oct-93	0.33	N/A	15-Oct-93
A - Plant / Rep 2	5	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 2	6	D - FG / 30 stations	24-Sep-93	0.33	N/A	8-Oct-93
A - Plant / Rep 2	7	D - FG / 30 stations	30-Sep-93	0.33	N/A	14-Oct-93
A - Plant / Rep 2	8	D - FG / 30 stations	28-Sep-93	0.33	N/A	12-Oct-93
A - Plant / Rep 2	9	D - FG / 30 stations	1-Jul-93	0.33	N/A	15-Oct-93
A - Plant / Rep 2	10	D - FG / 30 stations	20-Sep-93	0.33	N/A	4-Oct-93
A - Plant / Rep 3	1	D - FG / 30 stations	28-Sep-93	0.33	N/A	12-Oct-93
A - Plant / Rep 3	2	D - FG / 30 stations	29-Sep-93	0.33	N/A	13-Oct-93
A - Plant / Rep 3	3	D - FG / 30 stations	1-Oct-93	0.33	N/A	15-Oct-93
A - Plant / Rep 3	4	D - FG / 30 stations	21-Sep-93	0.33	N/A	5-Oct-93
A - Plant / Rep 3	5	D - FG / 30 stations	30-Sep-93	0.33	N/A	14-Oct-93
A - Plant / Rep 3	6	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 3	7	D - FG / 30 stations	21-Sep-93	0.33	N/A	5-Oct-93
A - Plant / Rep 3	8	D - FG / 30 stations	27-Sep-93	0.33	N/A	11-Oct-93
A - Plant / Rep 3	9	D - FG / 30 stations	24-Sep-93	0.33	N/A	8-Oct-93
A - Plant / Rep 3	10	D - FG / 30 stations	29-Sep-93	0.33	N/A	13-Oct-93
A - Plant / Rep 4	1	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 4	2	D - FG / 30 stations	1-Oct-93	0.33	N/A	15-Oct-93
A - Plant / Rep 4	3	D - FG / 30 stations	20-Sep-93	0.33	N/A	4-Oct-93
A - Plant / Rep 4	4	D - FG / 30 stations	28-Sep-93	0.33	N/A	12-Oct-93
A - Plant / Rep 4	5	D - FG / 30 stations	24-Sep-93	0.33	N/A	8-Oct-93
A - Plant / Rep 4	6	D - FG / 30 stations	23-Sep-93	0.33	N/A	7-Oct-93
A - Plant / Rep 4	7	D - FG / 30 stations	30-Sep-93	0.33	N/A	14-Oct-93
A - Plant / Rep 4	8	D - FG / 30 stations	22-Sep-93	0.33	N/A	6-Oct-93
A - Plant / Rep 4	9	D - FG / 30 stations	24-Sep-93	0.33	N/A	8-Oct-93
A - Plant / Rep 4	10	D - FG / 30 stations	27-Sep-93	0.33	N/A	11-Oct-93

T Plant Due Dates

Plant Type / Replication #	Job Order #	Product Type / # Process Stations (Sampled Without Relacement)	Arrival Date (Sampled With Replacement)	Constant (days/station)	Calculated Due Date (Initial)	Calculated Due Date (Final)
T - Plant / Rep 1	1	B - FG / 14 stations	24-Sep-93	0.58	N/A	7-Oct-93
T - Plant / Rep 1	2	G - FG / 15 stations	1-Oct-93	0.58	14-Oct-93	15-Oct-93
T - Plant / Rep 1	3	F - FG / 10 stations	29-Sep-93	0.58	N/A	7-Oct-93
T - Plant / Rep 1	4	C - FG / 17 stations	28-Sep-93	0.58	N/A	12-Oct-93
T - Plant / Rep 1	5	D - FG / 12 stations	20-Sep-93	0.58	29-Sep-93	11-Oct-93
T - Plant / Rep 1	6	D - FG / 12 stations	21-Sep-93	0.58	30-Sep-93	12-Oct-93
T - Plant / Rep 1	7	G - FG / 15 stations	20-Sep-93	0.58	1-Oct-93	14-Oct-93
T - Plant / Rep 1	8	B - FG / 14 stations	21-Sep-93	0.58	N/A	4-Oct-93
T - Plant / Rep 1	9	C - FG / 17 stations	21-Sep-93	0.58	N/A	5-Oct-93
T - Plant / Rep 1	10	F - FG / 10 stations	30-Sep-93	0.58	N/A	8-Oct-93
T - Plant / Rep 2	1	C - FG / 17 stations	20-Sep-93	0.58	N/A	5-Oct-93
T - Plant / Rep 2	2	B - FG / 14 stations	28-Sep-93	0.58	N/A	11-Oct-93
T - Plant / Rep 2	3	G - FG / 15 stations	21-Sep-93	0.58	N/A	5-Oct-93
T - Plant / Rep 2	4	D - FG / 12 stations	23-Sep-93	0.58	N/A	4-Oct-93
T - Plant / Rep 2	5	F - FG / 10 stations	21-Sep-93	0.58	29-Sep-93	7-Oct-93
T - Plant / Rep 2	6	G - FG / 15 stations	23-Sep-93	0.58	N/A	6-Oct-93
T - Plant / Rep 2	7	B - FG / 14 stations	24-Sep-93	0.58	N/A	7-Oct-93
T - Plant / Rep 2	8	C - FG / 17 stations	27-Sep-93	0.58	11-Oct-93	15-Oct-93
T - Plant / Rep 2	9	F - FG / 10 stations	30-Sep-93	0.58	N/A	8-Oct-93
T - Plant / Rep 2	10	D - FG / 12 stations	30-Sep-93	0.58	N/A	11-Oct-93
T - Plant / Rep 3	1	F - FG / 10 stations	29-Sep-93	0.58	N/A	7-Oct-93
T - Plant / Rep 3	2	G - FG / 15 stations	20-Sep-93	0.58	1-Oct-93	14-Oct-93
T - Plant / Rep 3	3	C - FG / 17 stations	1-Oct-93	0.58	N/A	15-Oct-93
T - Plant / Rep 3	4	B - FG / 14 stations	30-Sep-93	0.58	N/A	13-Oct-93
T - Plant / Rep 3	5	D - FG / 12 stations	28-Sep-93	0.58	N/A	7-Oct-93
T - Plant / Rep 3	6	B - FG / 14 stations	20-Sep-93	0.58	1-Oct-93	14-Oct-93
T - Plant / Rep 3	7	C - FG / 17 stations	24-Sep-93	0.58	N/A	8-Oct-93
T - Plant / Rep 3	8	F - FG / 10 stations	20-Sep-93	0.58	28-Sep-93	6-Oct-93
T - Plant / Rep 3	9	D - FG / 12 stations	25-Sep-93	0.58	N/A	6-Oct-93
T - Plant / Rep 3	10	G - FG / 15 stations	30-Sep-93	0.58	N/A	13-Oct-93
T - Plant / Rep 4	1	G - FG / 15 stations	30-Sep-93	0.58	N/A	13-Oct-93
T - Plant / Rep 4	2	C - FG / 17 stations	20-Sep-93	0.58	N/A	4-Oct-93
T - Plant / Rep 4	3	F - FG / 10 stations	23-Sep-93	0.58	1-Oct-93	11-Oct-93
T - Plant / Rep 4	4	B - FG / 14 stations	1-Oct-93	0.58	N/A	14-Oct-93
T - Plant / Rep 4	5	D - FG / 12 stations	20-Sep-93	0.58	29-Sep-93	8-Oct-93
T - Plant / Rep 4	6	B - FG / 14 stations	1-Oct-93	0.58	N/A	14-Oct-93
T - Plant / Rep 4	7	D - FG / 12 stations	23-Sep-93	0.58	N/A	4-Oct-93
T - Plant / Rep 4	8	G - FG / 15 stations	28-Sep-93	0.58	N/A	11-Oct-93
T - Plant / Rep 4	9	F - FG / 10 stations	20-Sep-93	0.58	28-Sep-93	6-Oct-93
T - Plant / Rep 4	10	C - FG / 17 stations	1-Oct-93	0.58	N/A	15-Oct-93

V Plant Due Dates

Plant Type / Replication #	Job Order #	Product Type / # Process Stations (Sampled Without Relacement)	Arrival Date (Sampled With Replacement)	Constant (days/station)	Calculated Due Date (Initial)	Calculated Due Date (Final)
V - Plant / Rep 1	1	E - FG / 12 stations	24-Sep-93	0.83	N/A	8-Oct-93
V - Plant / Rep 1	2	B - FG / 8 stations	20-Sep-93	0.83	29-Sep-93	8-Oct-93
V - Plant / Rep 1	3	A - FG / 11 stations	24-Sep-93	0.83	N/A	8-Oct-93
V - Plant / Rep 1	4	G - FG / 9 stations	22-Sep-93	0.83	N/A	4-Oct-93
V - Plant / Rep 1	5	D - FG / 10 stations	20-Sep-93	0.83	1-Oct-93	15-Oct-93
V - Plant / Rep 1	6	A - FG / 11 stations	23-Sep-93	0.83	N/A	7-Oct-93
V - Plant / Rep 1	7	D - FG / 10 stations	1-Oct-93	0.83	N/A	14-Oct-93
V - Plant / Rep 1	8	G - FG / 9 stations	29-Sep-93	0.83	N/A	11-Oct-93
V - Plant / Rep 1	9	E - FG / 12 stations	27-Sep-93	0.83	N/A	11-Oct-93
V - Plant / Rep 1	10	B - FG / 8 stations	22-Sep-93	0.83	1-Oct-93	12-Oct-93
V - Plant / Rep 2	1	D - FG / 10 stations	29-Sep-93	0.83	N/A	12-Oct-93
V - Plant / Rep 2	2	B - FG / 8 stations	1-Oct-93	0.83	N/A	12-Oct-93
V - Plant / Rep 2	3	A - FG / 11 stations	29-Sep-93	0.83	N/A	13-Oct-93
V - Plant / Rep 2	4	G - FG / 9 stations	30-Sep-93	0.83	N/A	12-Oct-93
V - Plant / Rep 2	5	E - FG / 12 stations	20-Sep-93	0.83	N/A	4-Oct-93
V - Plant / Rep 2	6	A - FG / 11 stations	22-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 2	7	B - FG / 8 stations	27-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 2	8	E - FG / 12 stations	29-Sep-93	0.83	13-Oct-93	15-Oct-93
V - Plant / Rep 2	9	G - FG / 9 stations	28-Sep-93	0.83	N/A	8-Oct-93
V - Plant / Rep 2	10	D - FG / 10 stations	24-Sep-93	0.83	N/A	7-Oct-93
V - Plant / Rep 3	1	D - FG / 10 stations	29-Sep-93	0.83	N/A	12-Oct-93
V - Plant / Rep 3	2	E - FG / 12 stations	1-Oct-93	0.83	N/A	15-Oct-93
V - Plant / Rep 3	3	B - FG / 8 stations	24-Sep-93	0.83	N/A	5-Oct-93
V - Plant / Rep 3	4	A - FG / 11 stations	1-Oct-93	0.83	N/A	15-Oct-93
V - Plant / Rep 3	5	G - FG / 9 stations	22-Sep-93	0.83	N/A	4-Oct-93
V - Plant / Rep 3	6	E - FG / 12 stations	1-Oct-93	0.83	N/A	15-Oct-93
V - Plant / Rep 3	7	A - FG / 11 stations	28-Sep-93	0.83	N/A	12-Oct-93
V - Plant / Rep 3	8	D - FG / 10 stations	23-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 3	9	B - FG / 8 stations	22-Sep-93	0.83	1-Oct-93	12-Oct-93
V - Plant / Rep 3	10	G - FG / 9 stations	20-Sep-93	0.83	30-Sep-93	12-Oct-93
V - Plant / Rep 4	1	B - FG / 8 stations	27-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 4	2	G - FG / 9 stations	23-Sep-93	0.83	N/A	5-Oct-93
V - Plant / Rep 4	3	E - FG / 12 stations	22-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 4	4	A - FG / 11 stations	20-Sep-93	0.83	N/A	4-Oct-93
V - Plant / Rep 4	5	D - FG / 10 stations	27-Sep-93	0.83	8-Oct-93	15-Oct-93
V - Plant / Rep 4	6	D - FG / 10 stations	27-Sep-93	0.83	N/A	8-Oct-93
V - Plant / Rep 4	7	A - FG / 11 stations	21-Sep-93	0.83	N/A	5-Oct-93
V - Plant / Rep 4	8	G - FG / 9 stations	24-Sep-93	0.83	N/A	6-Oct-93
V - Plant / Rep 4	9	E - FG / 12 stations	23-Sep-93	0.83	N/A	7-Oct-93
V - Plant / Rep 4	10	B - FG / 8 stations	28-Sep-93	0.83	N/A	7-Oct-93

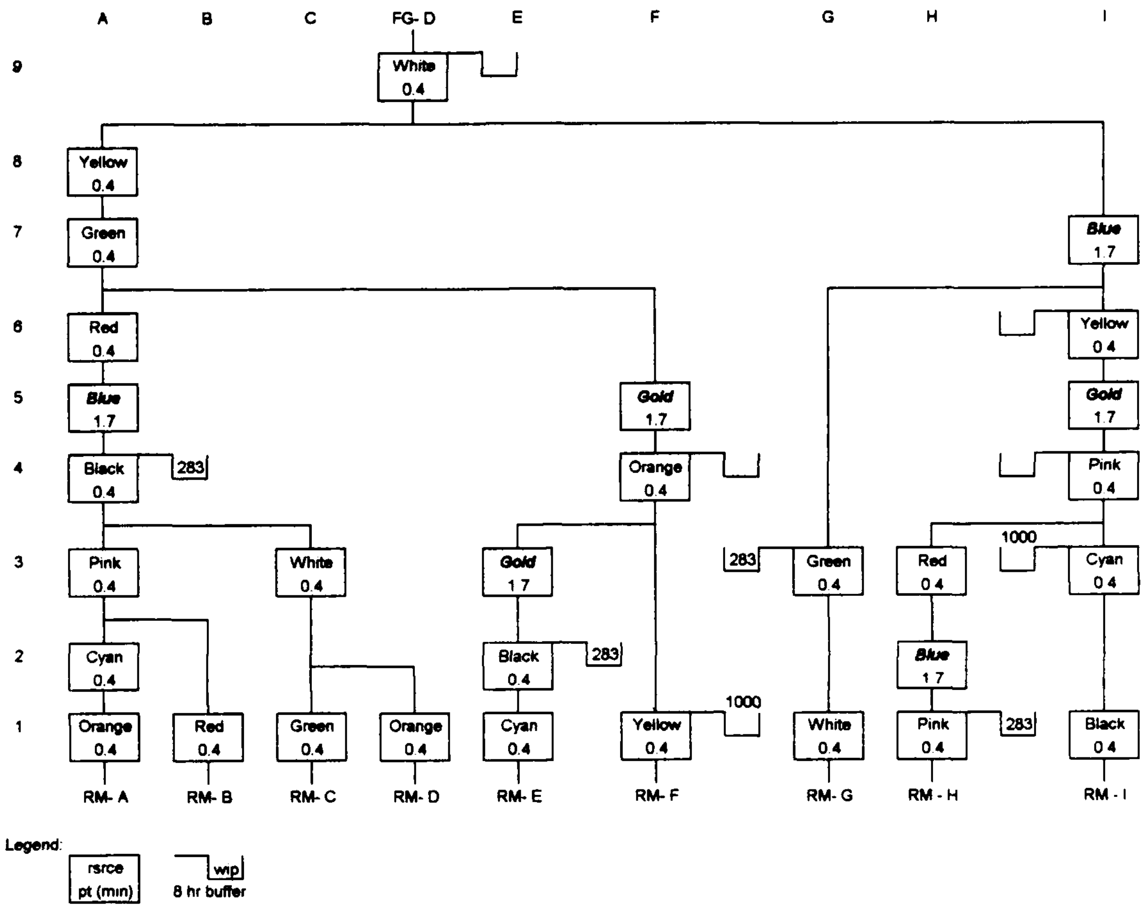
Appendix C: Network Representation of Benchmark Problems

General Notes

1) Legend: Note that each box represents a process station in the production operation. In each box, the top line identifies the resource type and the bottom line identifies the processing time per unit (in minutes). The "frying pans" next to some of the process stations represent eight hour buffers. Any number inside the "frying pan" represents the amount of WIP **already processed** by that station. Connecting lines between process stations represent the flow of material through the operation from bottom to top of the page.

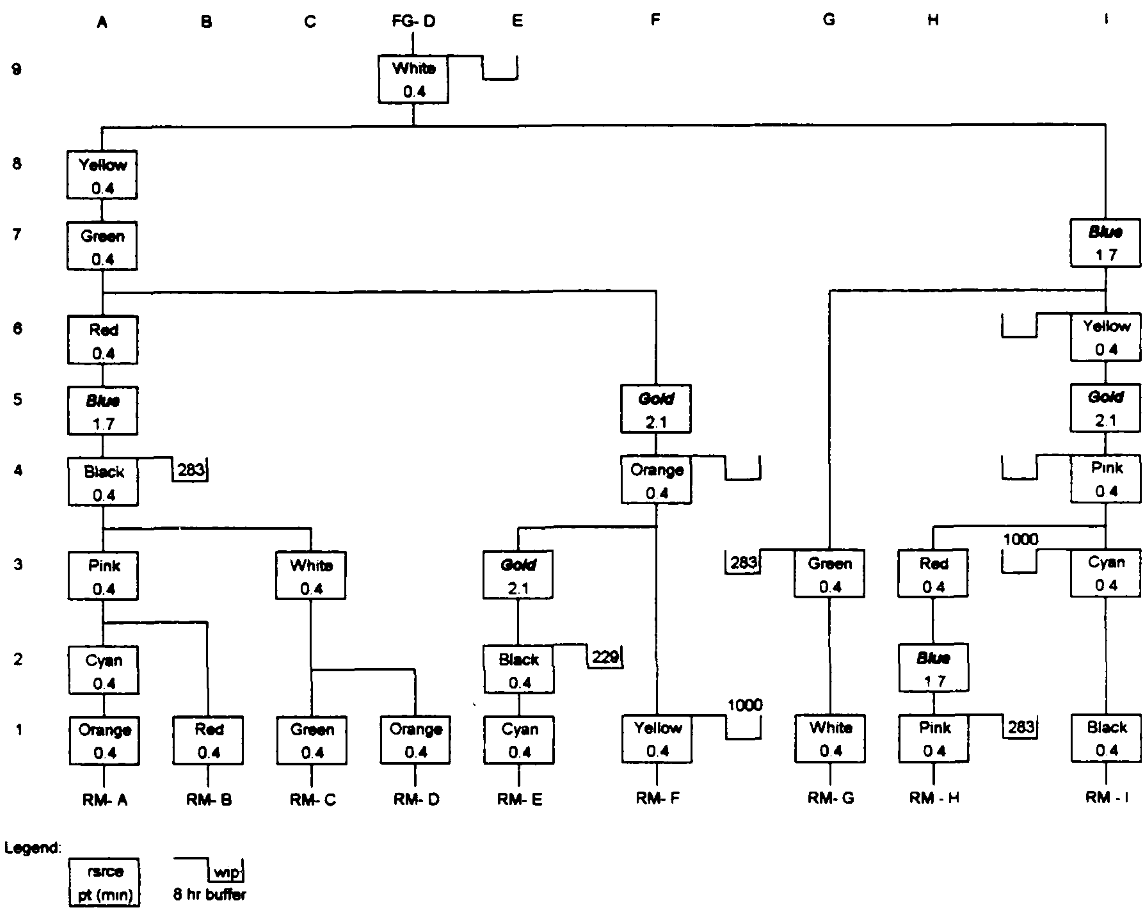
2) Job Order Replication Listings: These are self-explanatory with the exception of the asterisks (*) which appear next to some due dates. These asterisks represent the situation where two job orders of the same product type are due on the same day. In these cases, in order to input the job order due dates into *DISASTER™*, one must combine the two job orders into one.

A Plant, %RCF=105%, %ΔRCF=0%



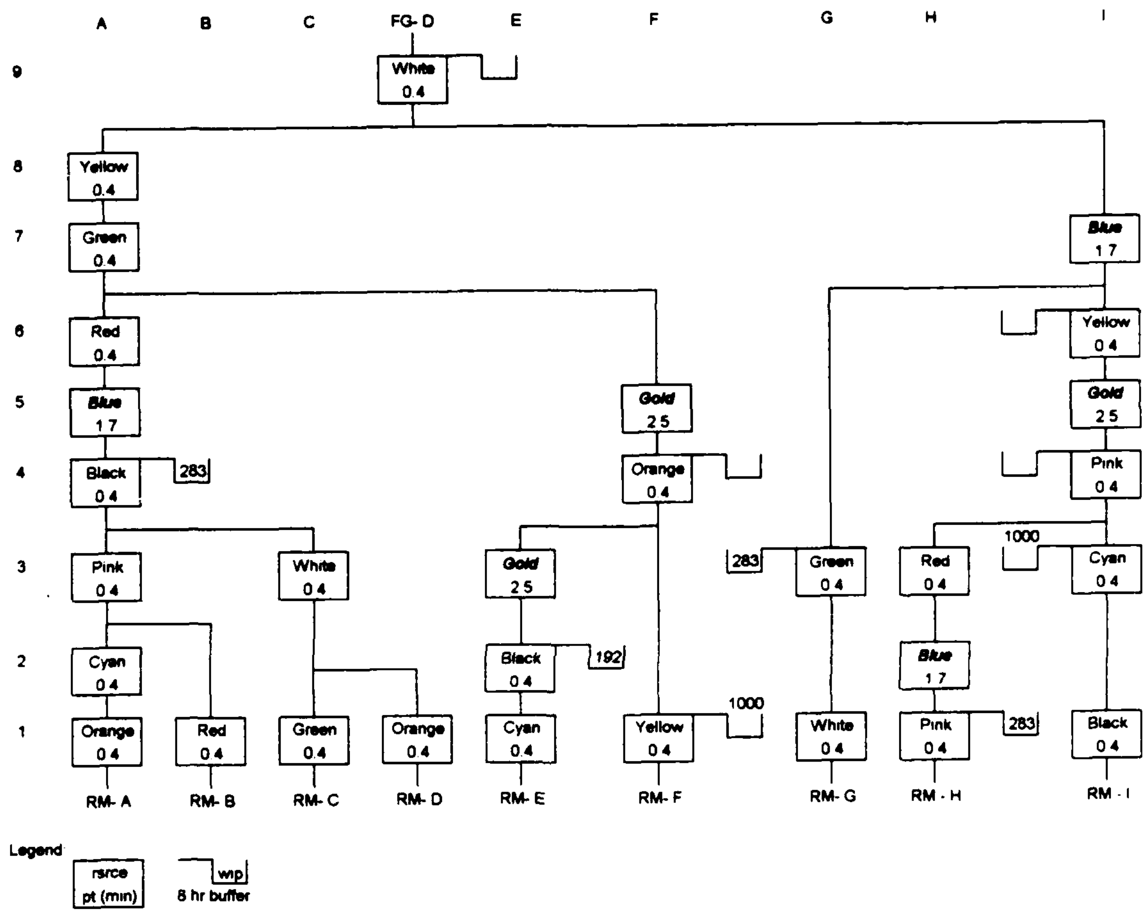
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	* 05 Oct 93	FG - D	04 Oct 93
FG - D	* 05 Oct 93	FG - D	* 07 Oct 93	FG - D	* 05 Oct 93	FG - D	06 Oct 93
FG - D	* 05 Oct 93	FG - D	* 07 Oct 93	FG - D	07 Oct 93	FG - D	* 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	* 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	* 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	* 08 Oct 93
FG - D	* 13 Oct 93	FG - D	* 14 Oct 93	FG - D	* 13 Oct 93	FG - D	11 Oct 93
FG - D	* 13 Oct 93	FG - D	* 14 Oct 93	FG - D	* 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	* 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	* 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=105%, %ΔRCF=25%



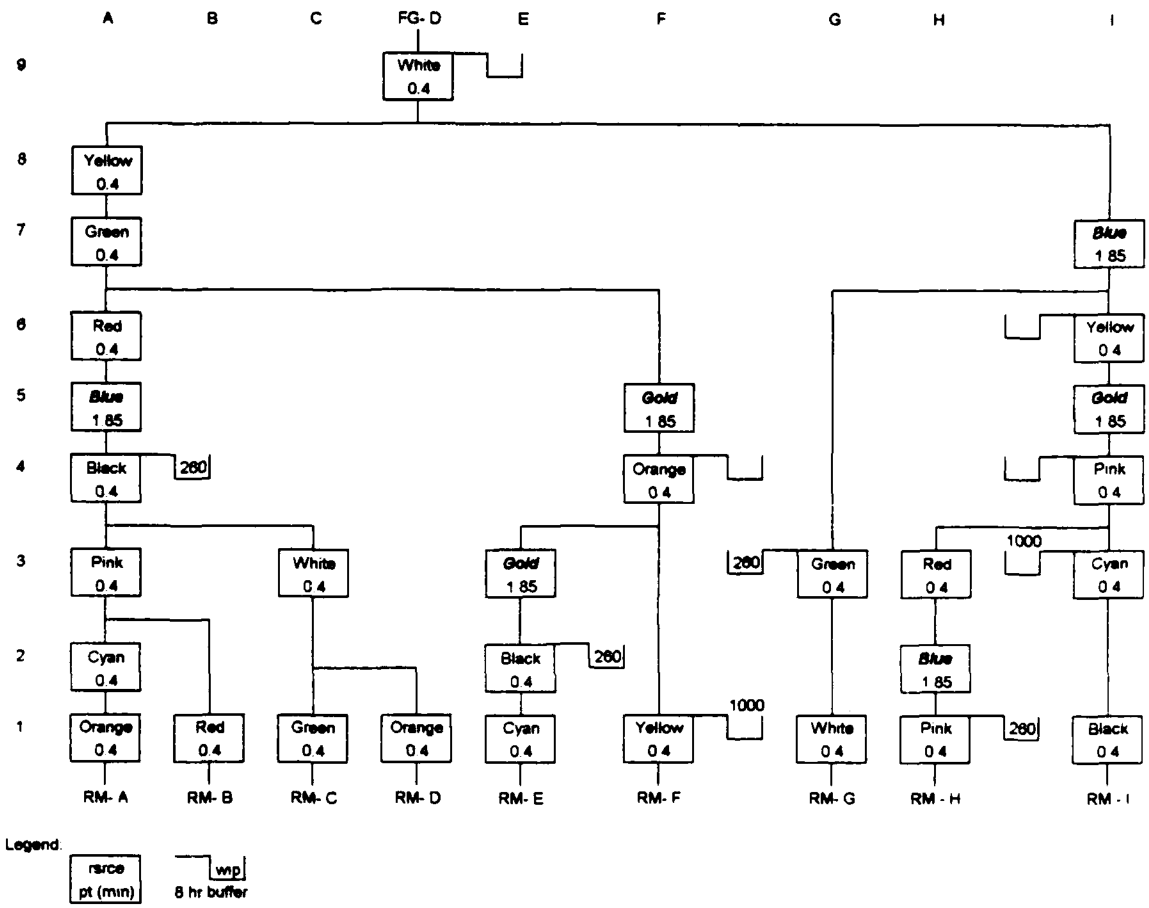
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	**Due Date**	**Product Type**	**Due Date**	**Product Type**	**Due Date**	**Product Type**	**Due Date**
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 05 Oct 93	FG - D	06 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=105%, %ΔRCF=50%



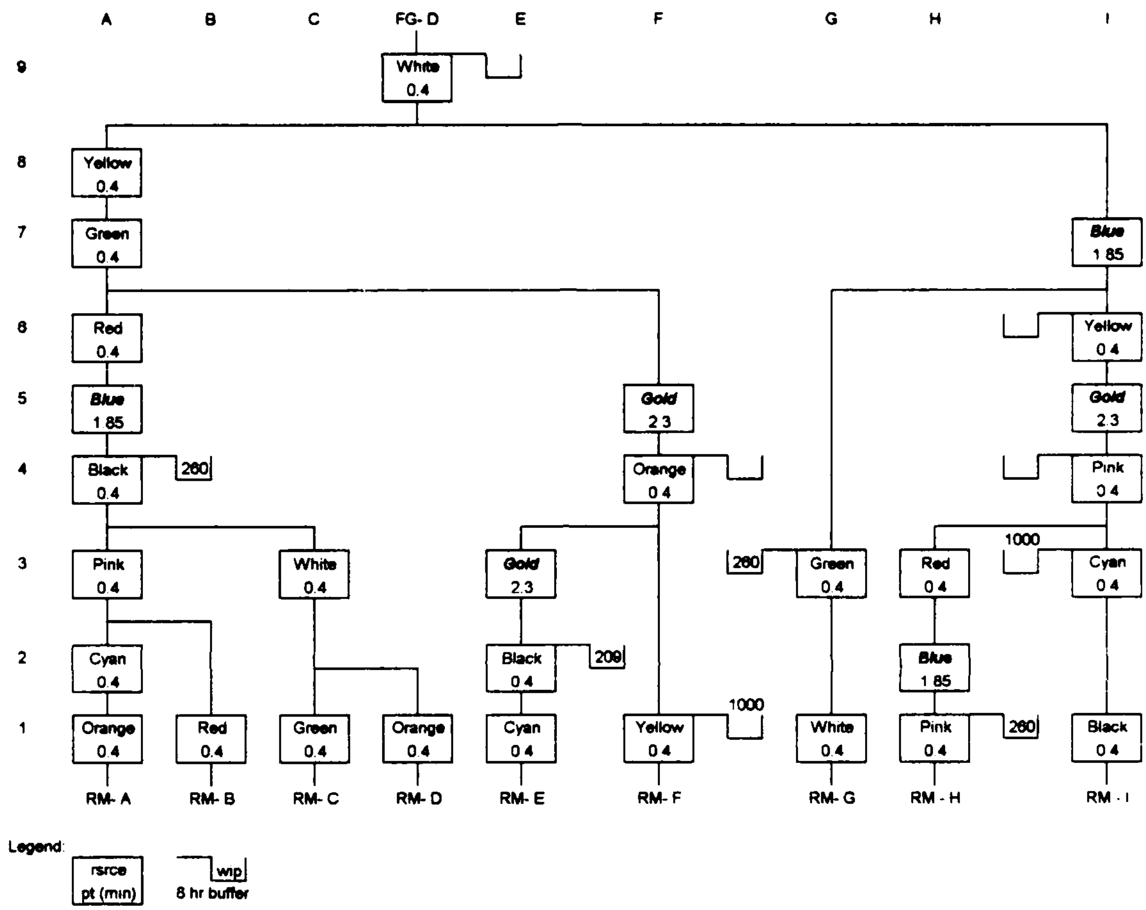
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 05 Oct 93	FG - D	06 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=115%, %ΔRCF=0%



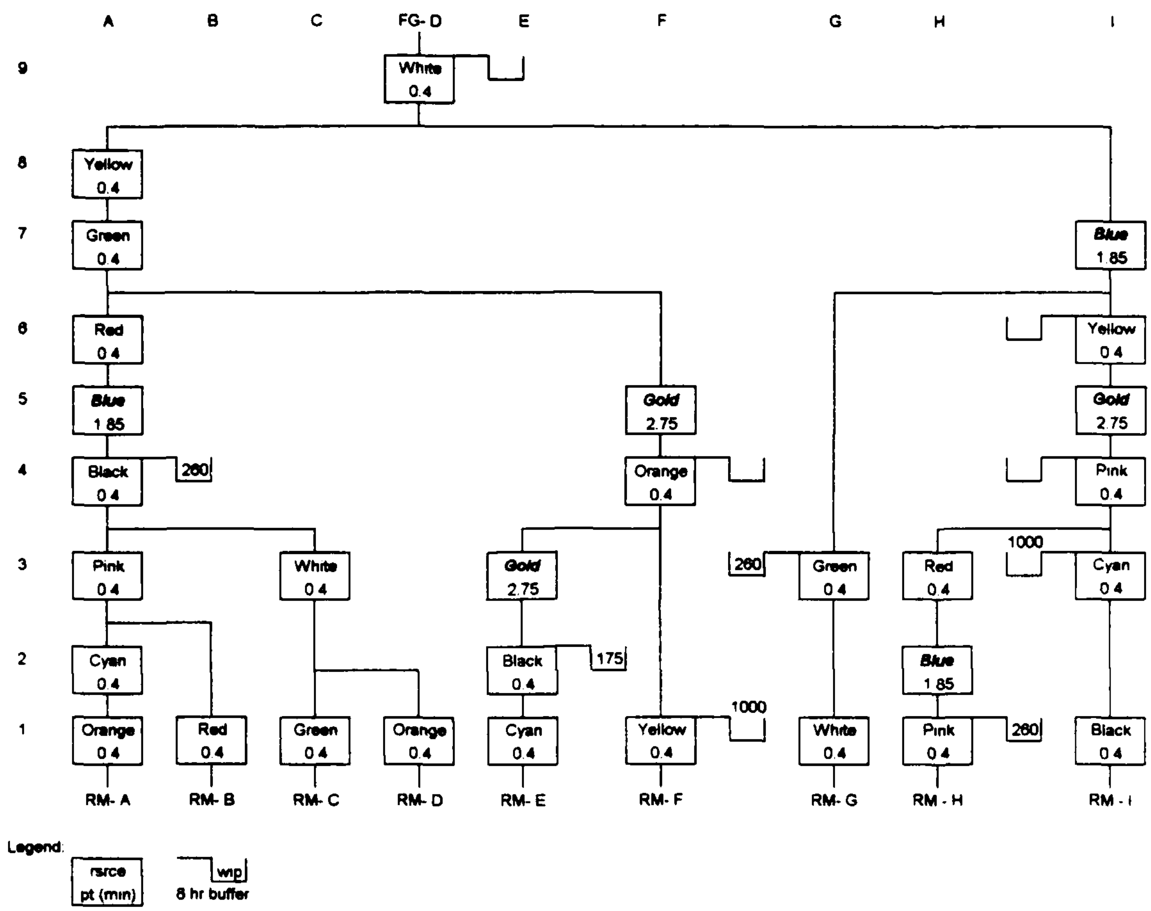
Job Orders Rep 1			Job Orders Rep 2			Job Orders Rep 3			Job Orders Rep 4		
Product Type		**Due Date**	**Product Type**		**Due Date**	**Product Type**		**Due Date**	**Product Type**		**Due Date**
FG - D		04 Oct 93	FG - D		04 Oct 93	FG - D	*	05 Oct 93	FG - D		04 Oct 93
FG - D	*	05 Oct 93	FG - D	*	07 Oct 93	FG - D	*	05 Oct 93	FG - D		06 Oct 93
FG - D	*	05 Oct 93	FG - D	*	07 Oct 93	FG - D		07 Oct 93	FG - D	*	07 Oct 93
FG - D		06 Oct 93	FG - D		08 Oct 93	FG - D		08 Oct 93	FG - D	*	07 Oct 93
FG - D		07 Oct 93	FG - D		12 Oct 93	FG - D		11 Oct 93	FG - D	*	08 Oct 93
FG - D		11 Oct 93	FG - D		13 Oct 93	FG - D		12 Oct 93	FG - D	*	08 Oct 93
FG - D	*	13 Oct 93	FG - D	*	14 Oct 93	FG - D	*	13 Oct 93	FG - D		11 Oct 93
FG - D	*	13 Oct 93	FG - D	*	14 Oct 93	FG - D	*	13 Oct 93	FG - D		12 Oct 93
FG - D		14 Oct 93	FG - D	*	15 Oct 93	FG - D		14 Oct 93	FG - D		14 Oct 93
FG - D		15 Oct 93	FG - D	*	15 Oct 93	FG - D		15 Oct 93	FG - D		15 Oct 93

A Plant, %RCF=115%, %ΔRCF=25%



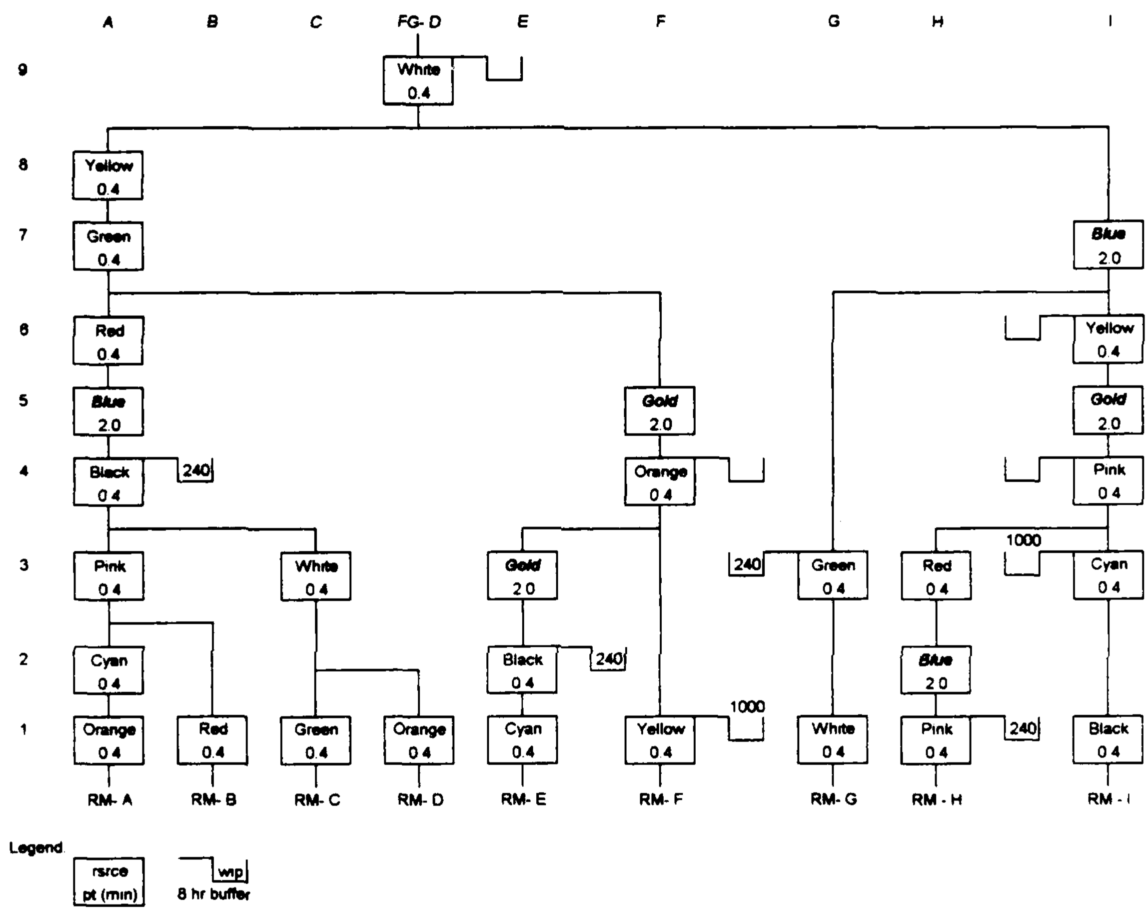
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	* 05 Oct 93	FG - D	04 Oct 93
FG - D	* 05 Oct 93	FG - D	* 07 Oct 93	FG - D	* 05 Oct 93	FG - D	06 Oct 93
FG - D	* 05 Oct 93	FG - D	* 07 Oct 93	FG - D	07 Oct 93	FG - D	* 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	* 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	* 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	* 08 Oct 93
FG - D	* 13 Oct 93	FG - D	* 14 Oct 93	FG - D	* 13 Oct 93	FG - D	11 Oct 93
FG - D	* 13 Oct 93	FG - D	* 14 Oct 93	FG - D	* 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	* 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	* 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=115%, %ΔRCF=50%



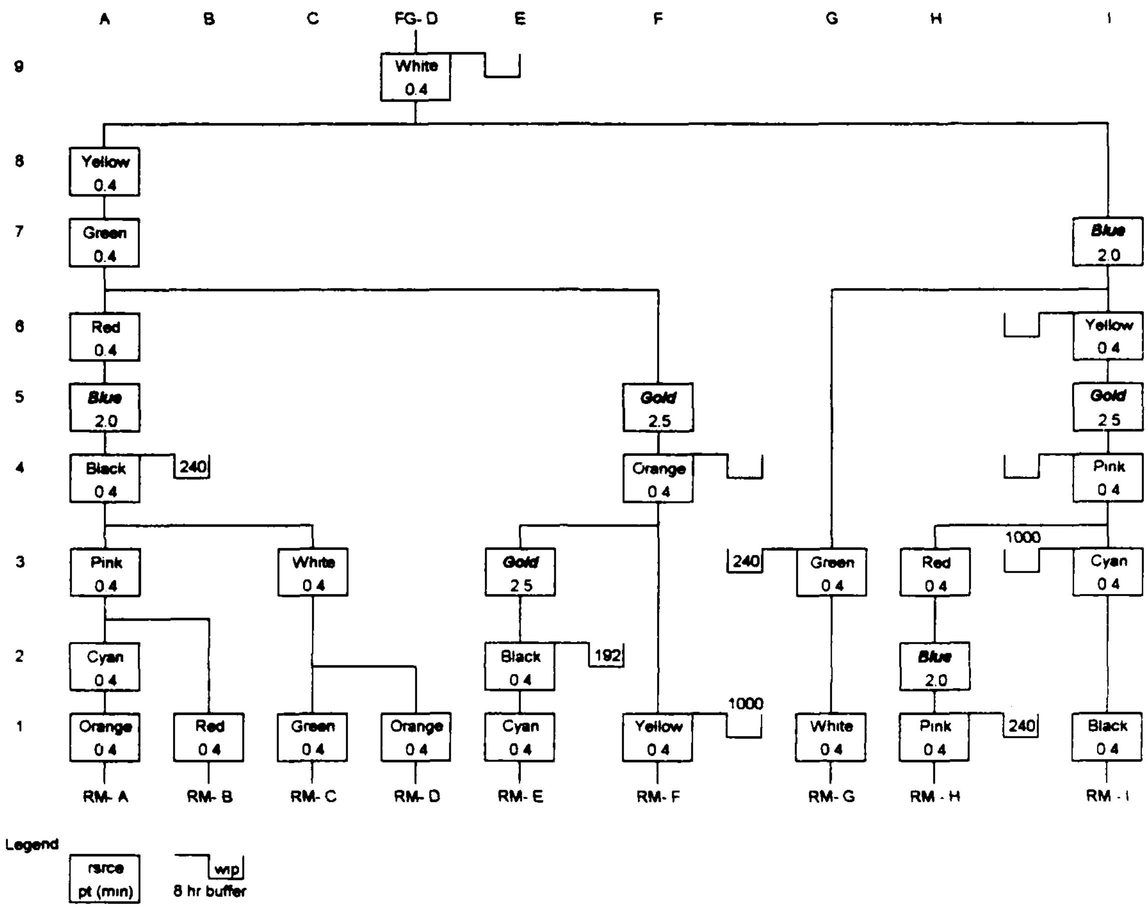
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 05 Oct 93	FG - D	06 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=125%, %ΔRCF=0%



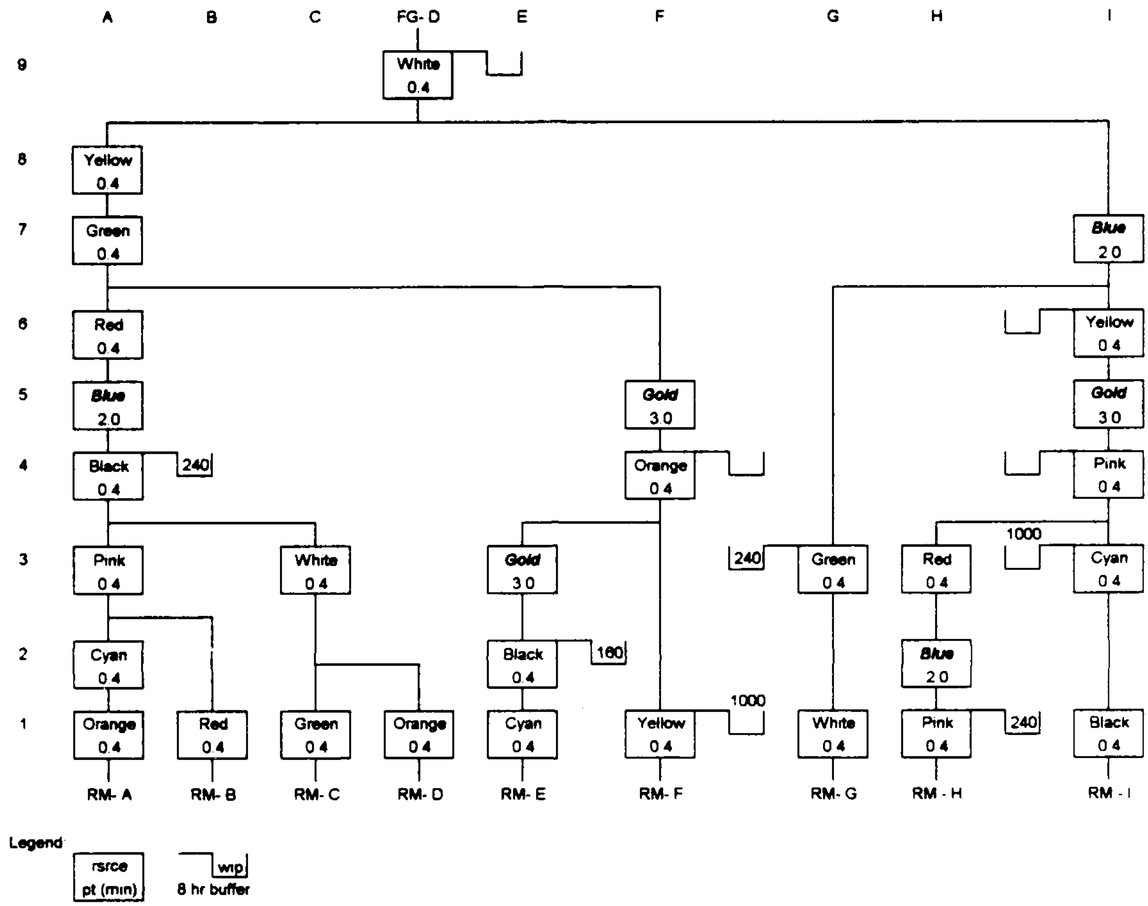
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 06 Oct 93	FG - D	06 Oct 93
FG - D	• 06 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=125%, %ΔRCF=25%



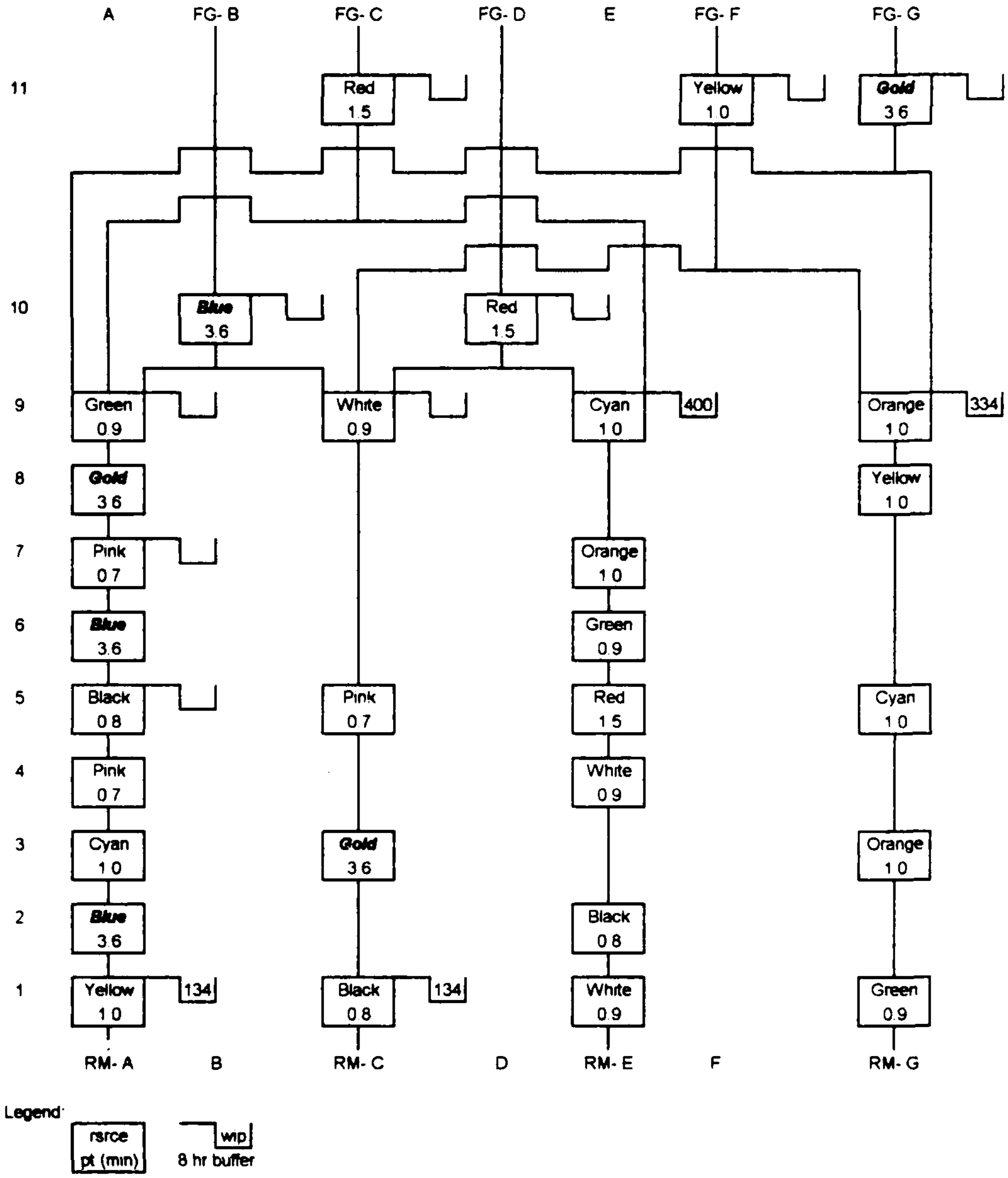
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 05 Oct 93	FG - D	06 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

A Plant, %RCF=125%, %ΔRCF=50%



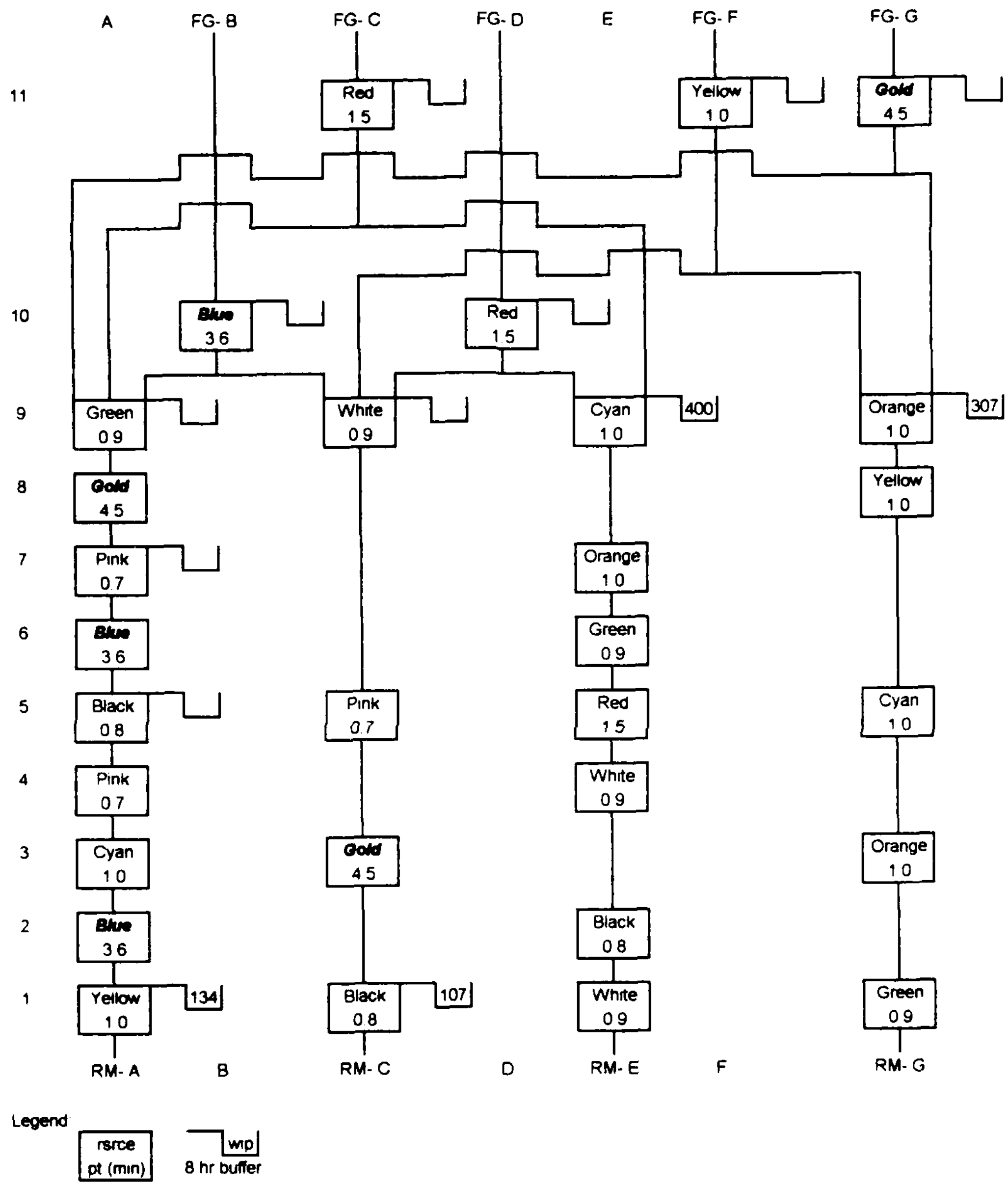
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - D	04 Oct 93	FG - D	04 Oct 93	FG - D	• 05 Oct 93	FG - D	04 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	• 05 Oct 93	FG - D	06 Oct 93
FG - D	• 05 Oct 93	FG - D	• 07 Oct 93	FG - D	07 Oct 93	FG - D	• 07 Oct 93
FG - D	06 Oct 93	FG - D	08 Oct 93	FG - D	08 Oct 93	FG - D	• 07 Oct 93
FG - D	07 Oct 93	FG - D	12 Oct 93	FG - D	11 Oct 93	FG - D	• 08 Oct 93
FG - D	11 Oct 93	FG - D	13 Oct 93	FG - D	12 Oct 93	FG - D	• 08 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	11 Oct 93
FG - D	• 13 Oct 93	FG - D	• 14 Oct 93	FG - D	• 13 Oct 93	FG - D	12 Oct 93
FG - D	14 Oct 93	FG - D	• 15 Oct 93	FG - D	14 Oct 93	FG - D	14 Oct 93
FG - D	15 Oct 93	FG - D	• 15 Oct 93	FG - D	15 Oct 93	FG - D	15 Oct 93

T Plant, %RCF=105%, %ΔRCF=0%



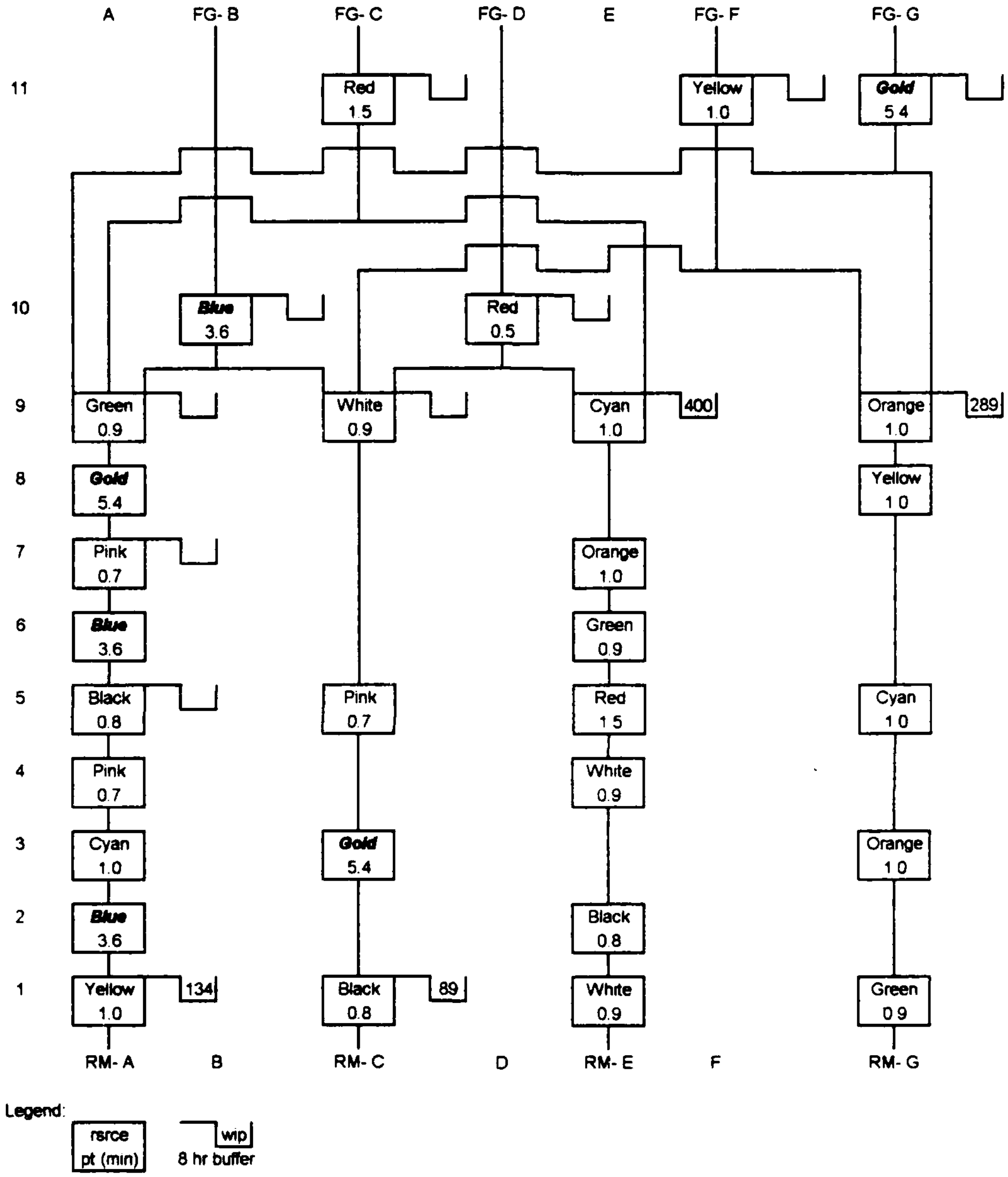
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=105%, %ΔRCF=25%



Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	• 14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	• 14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=105%, %ΔRCF=50%



Job Orders Rep 1

Product Type	Due Date
FG - B	04 Oct 93
FG - C	05 Oct 93
FG - B	07 Oct 93
FG - F	07 Oct 93
FG - F	08 Oct 93
FG - D	11 Oct 93
FG - C	12 Oct 93
FG - D	12 Oct 93
FG - G	14 Oct 93
FG - G	15 Oct 93

Job Orders Rep 2

Product Type	Due Date
FG - D	04 Oct 93
FG - G	05 Oct 93
FG - C	05 Oct 93
FG - G	06 Oct 93
FG - B	07 Oct 93
FG - F	07 Oct 93
FG - F	08 Oct 93
FG - B	11 Oct 93
FG - D	11 Oct 93
FG - C	15 Oct 93

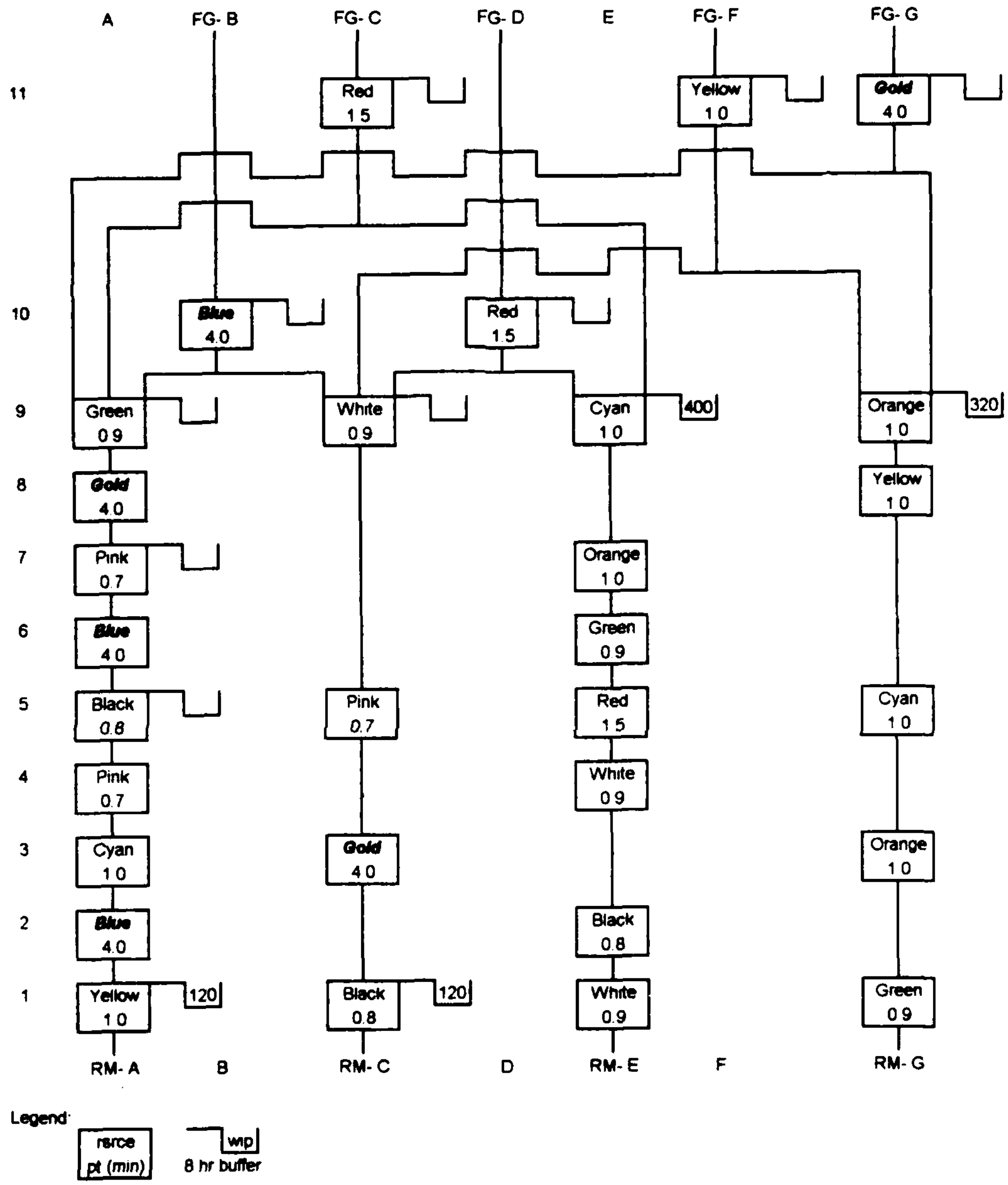
Job Orders Rep 3

Product Type	Due Date
FG - D	06 Oct 93
FG - F	06 Oct 93
FG - D	07 Oct 93
FG - F	07 Oct 93
FG - C	08 Oct 93
FG - B	13 Oct 93
FG - G	13 Oct 93
FG - B	14 Oct 93
FG - G	14 Oct 93
FG - C	15 Oct 93

Job Orders Rep 4

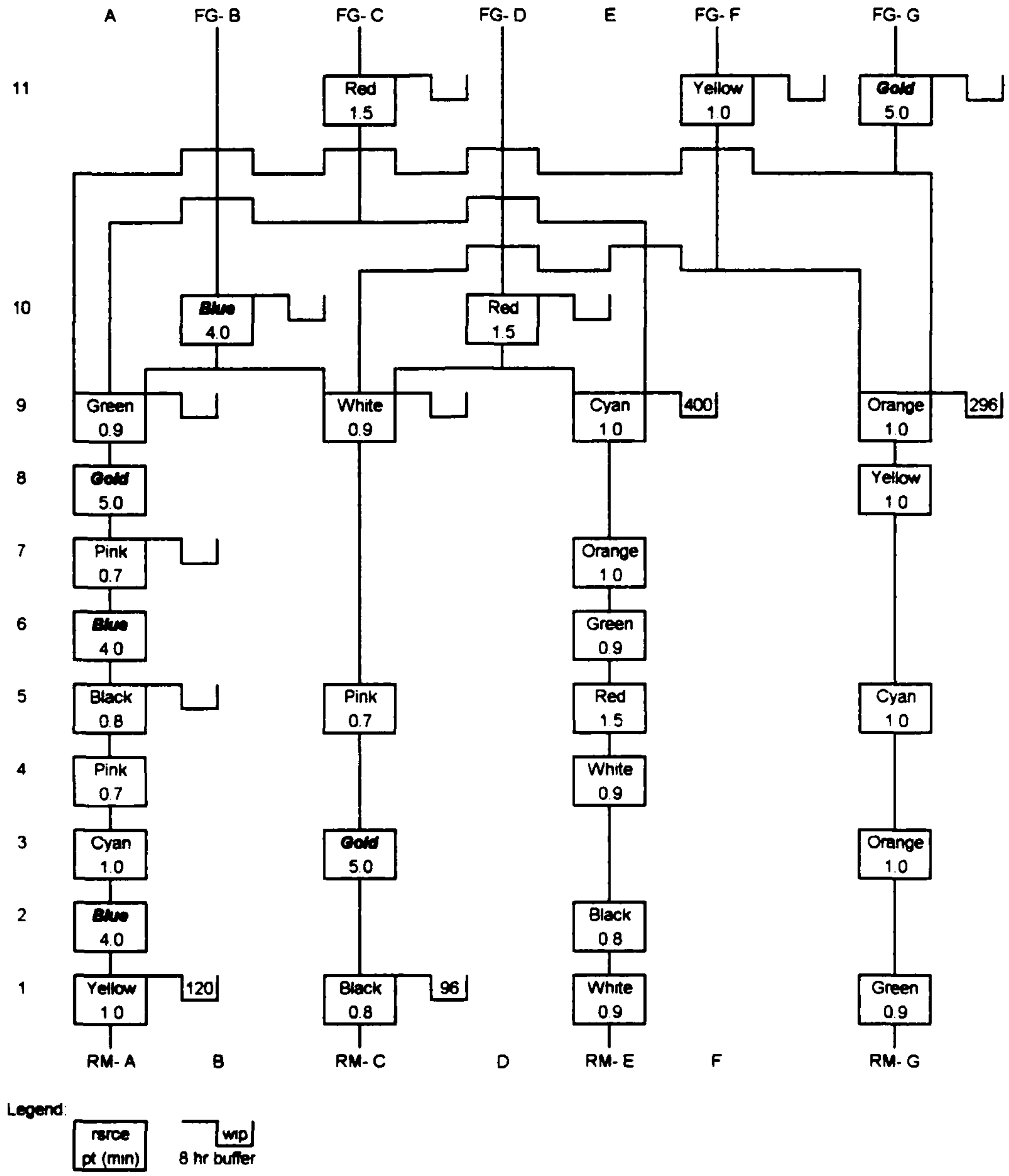
Product Type	Due Date
FG - C	04 Oct 93
FG - D	04 Oct 93
FG - F	06 Oct 93
FG - D	08 Oct 93
FG - F	11 Oct 93
FG - G	11 Oct 93
FG - G	13 Oct 93
FG - B	14 Oct 93
FG - B	14 Oct 93
FG - C	15 Oct 93

T Plant, %RCF=115%, %ΔRCF=0%



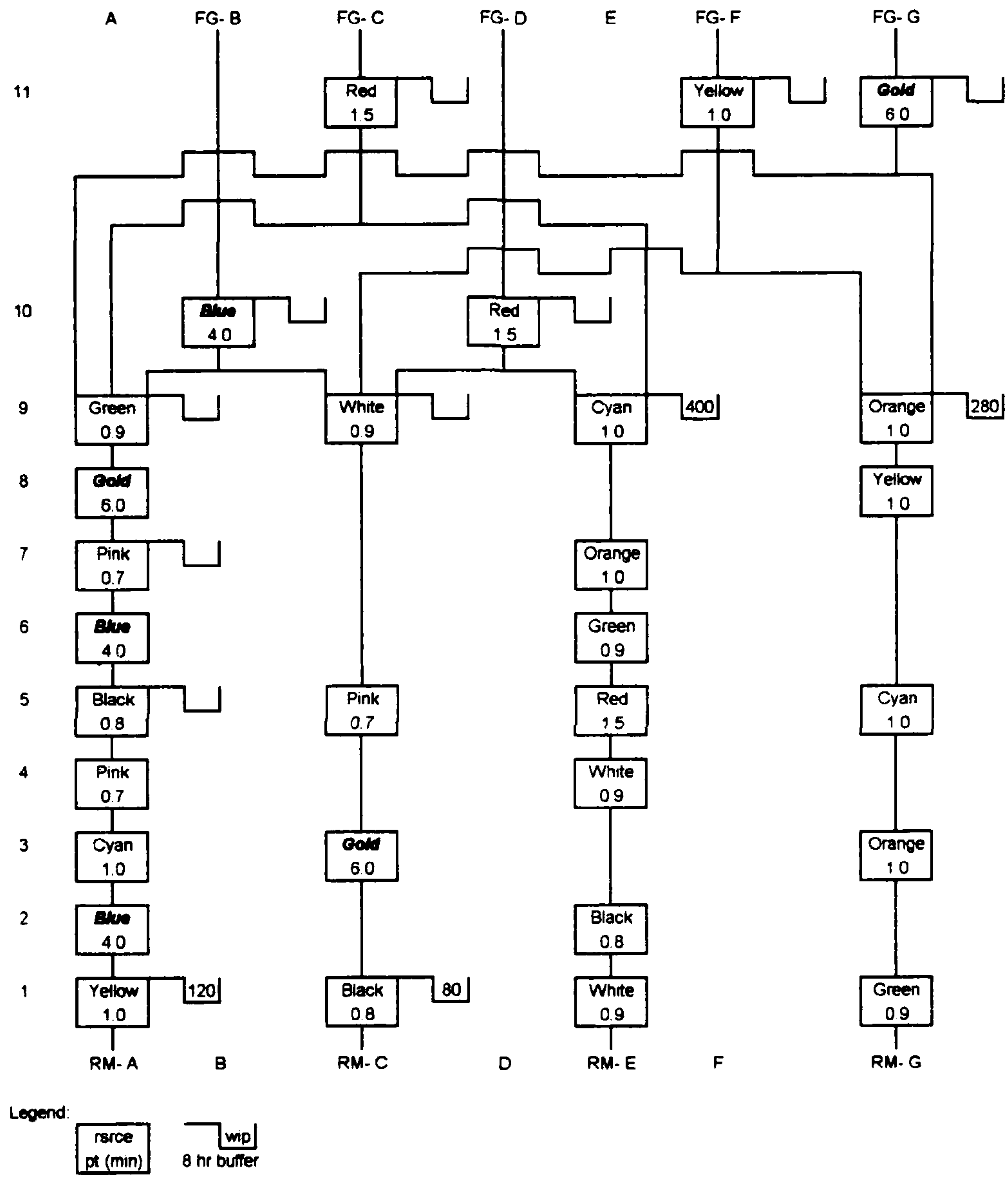
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=115%, %ΔRCF=25%



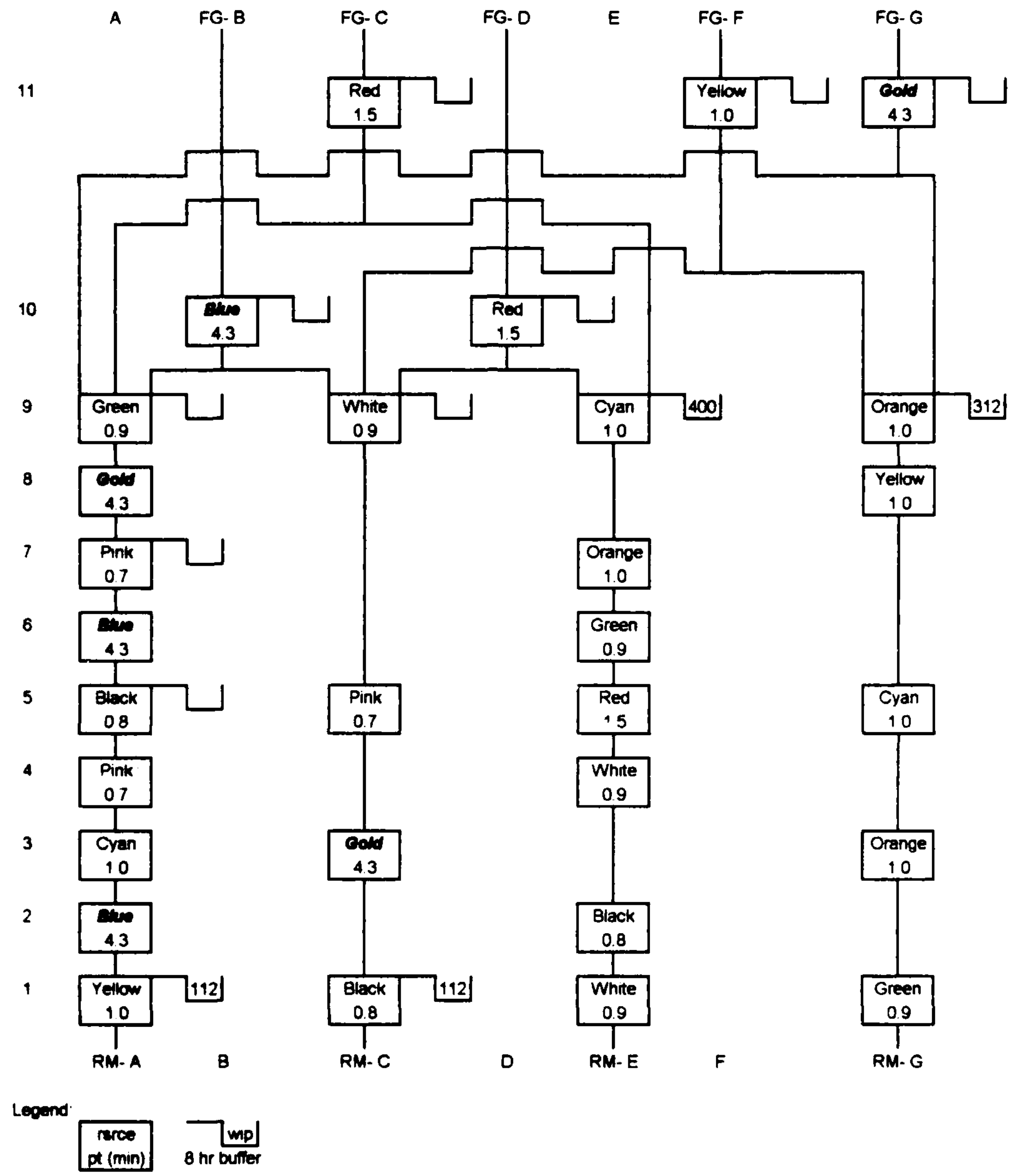
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	• 14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	• 14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=115%, %ΔRCF=50%



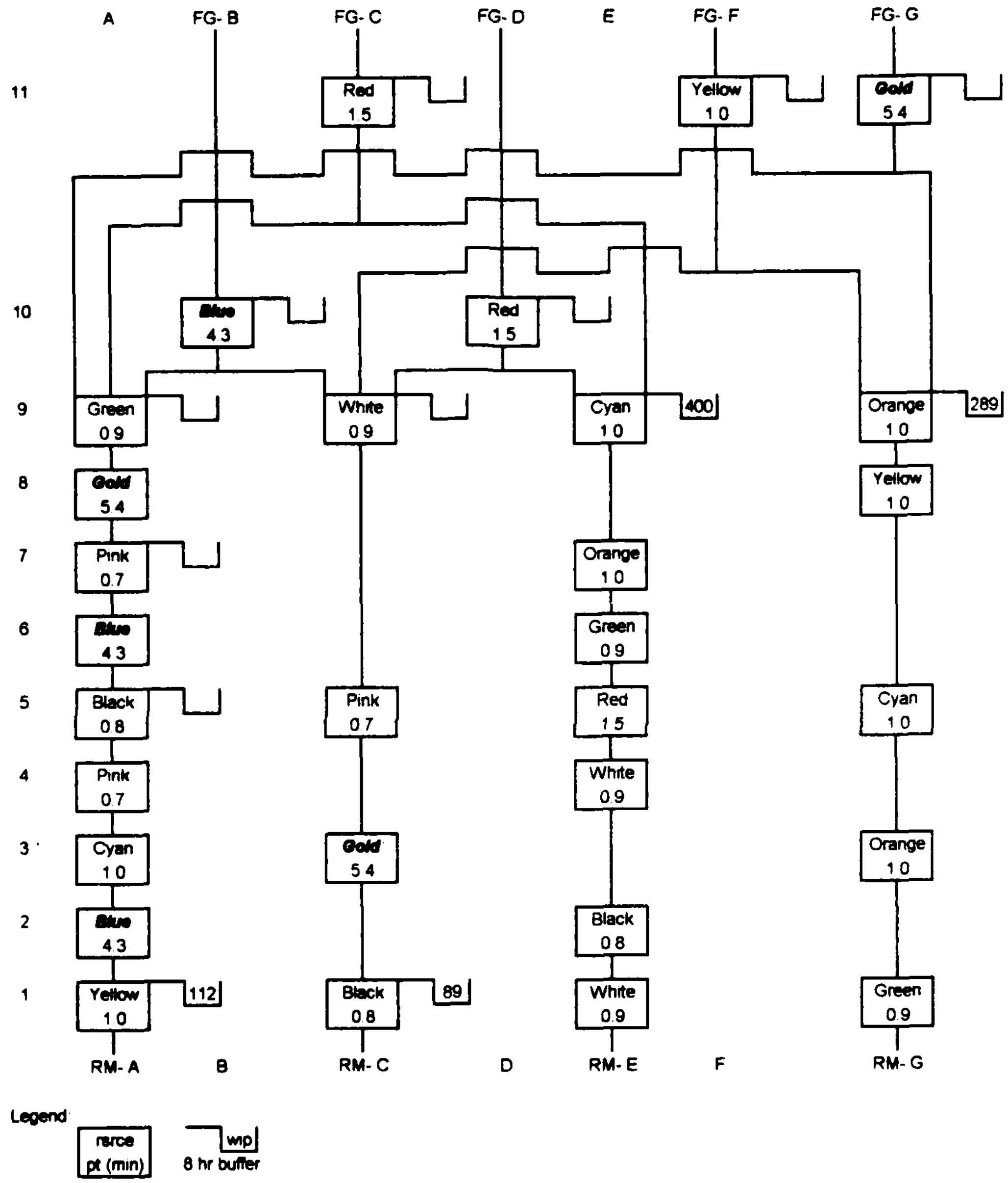
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=125%, %ΔRCF=0%



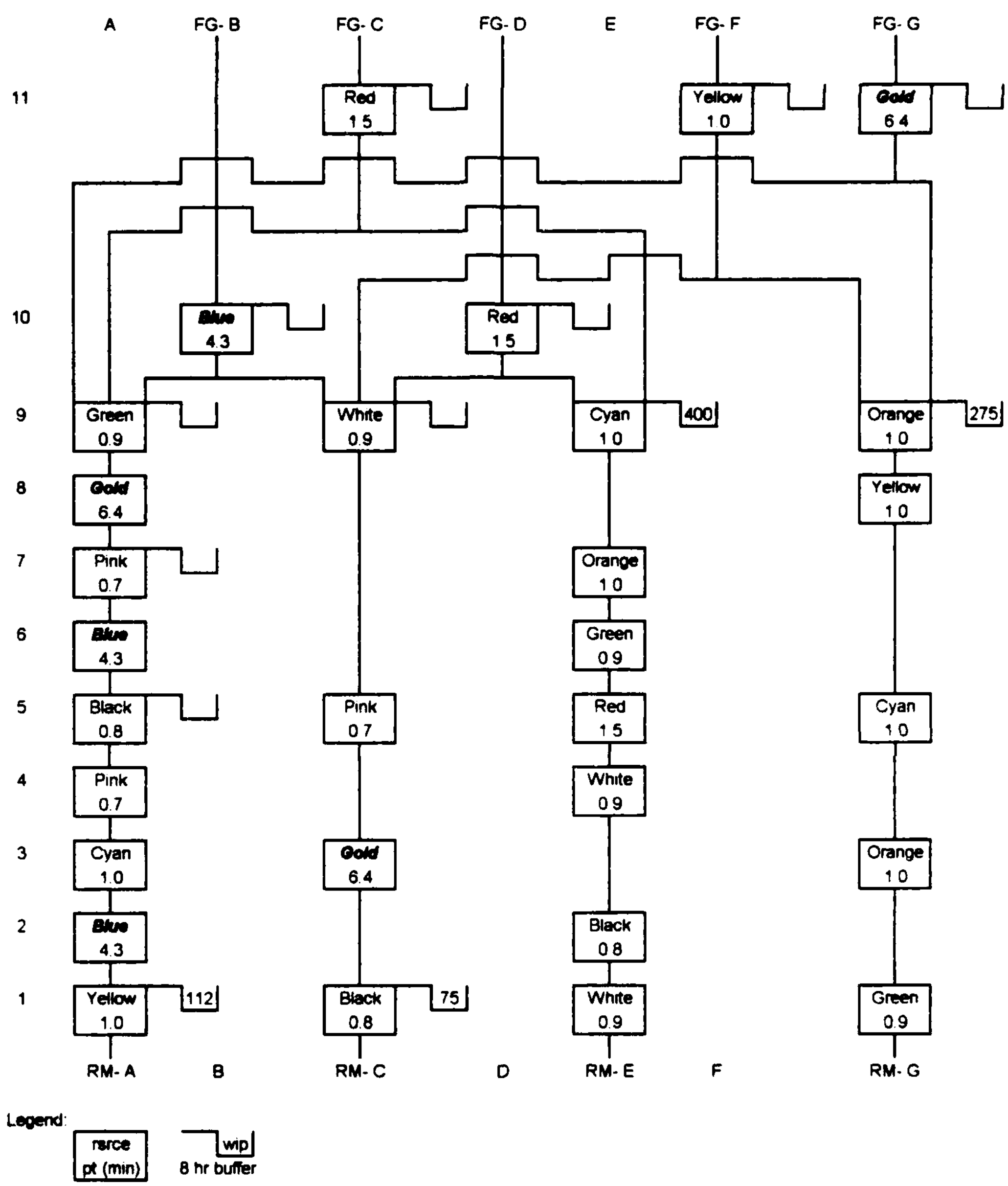
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=125%, %ΔRCF=25%



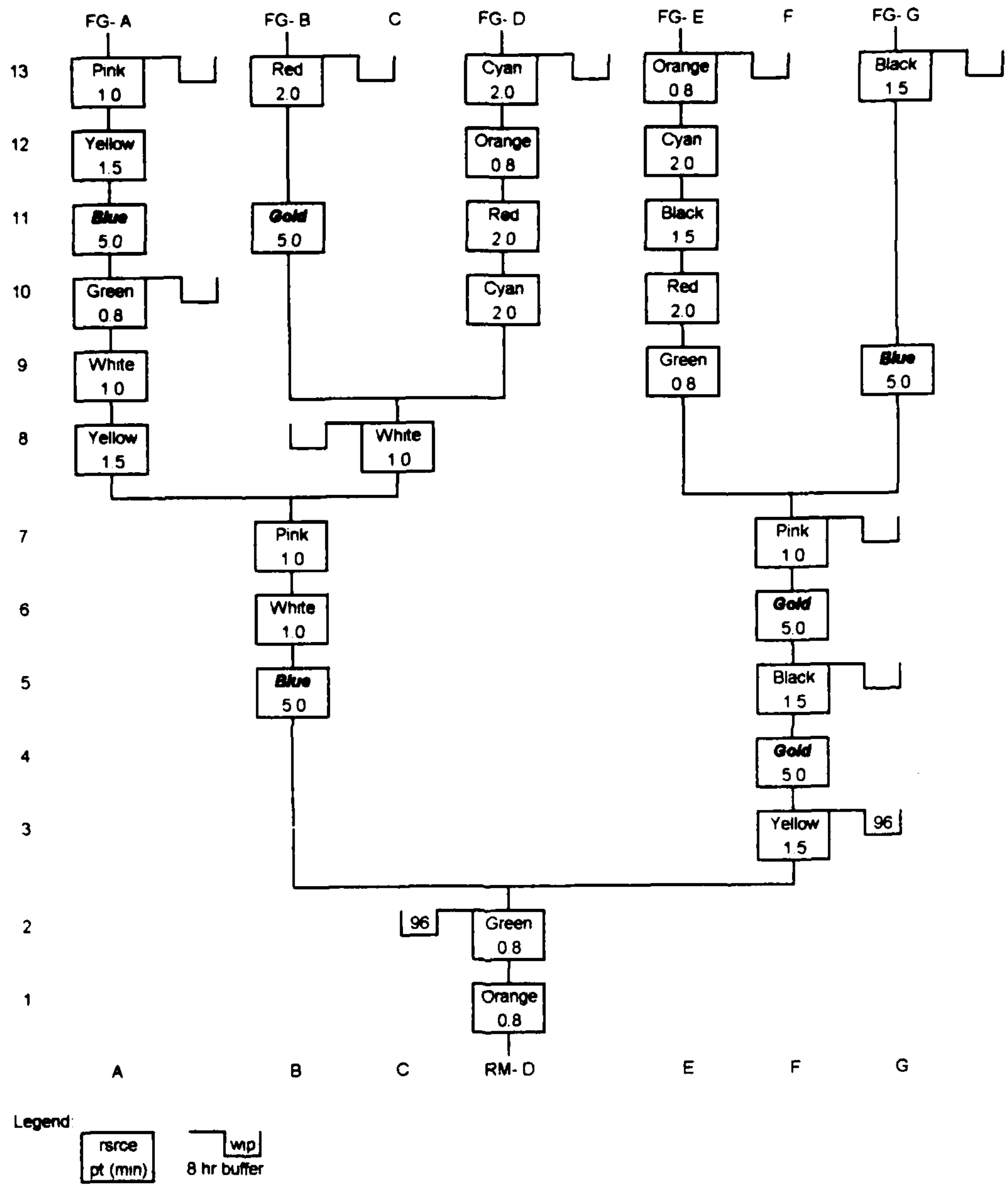
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

T Plant, %RCF=125%, %ΔRCF=50%



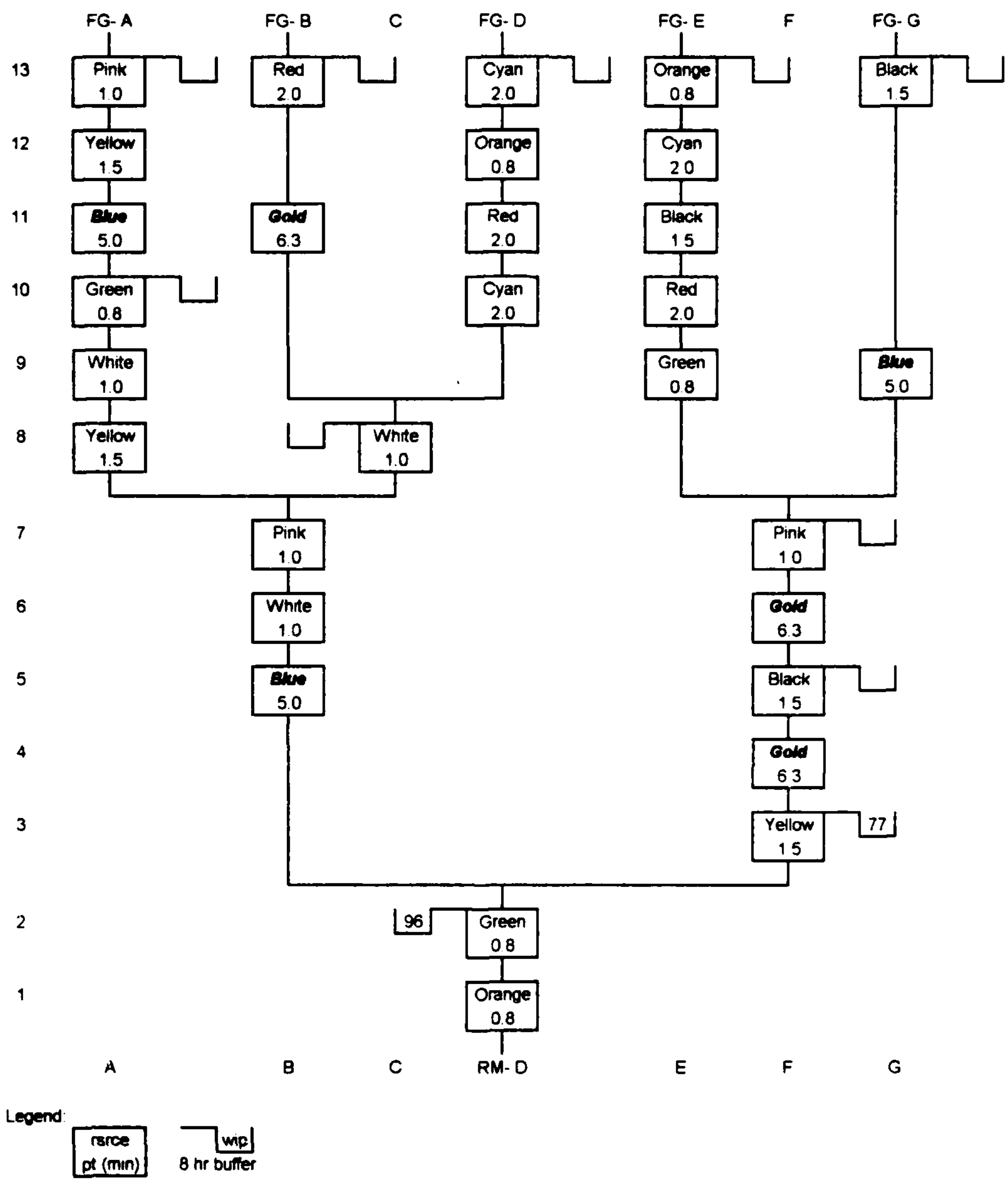
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - B	04 Oct 93	FG - D	04 Oct 93	FG - D	06 Oct 93	FG - C	04 Oct 93
FG - C	05 Oct 93	FG - G	05 Oct 93	FG - F	06 Oct 93	FG - D	04 Oct 93
FG - B	07 Oct 93	FG - C	05 Oct 93	FG - D	07 Oct 93	FG - F	06 Oct 93
FG - F	07 Oct 93	FG - G	06 Oct 93	FG - F	07 Oct 93	FG - D	08 Oct 93
FG - F	08 Oct 93	FG - B	07 Oct 93	FG - C	08 Oct 93	FG - F	11 Oct 93
FG - D	11 Oct 93	FG - F	07 Oct 93	FG - B	13 Oct 93	FG - G	11 Oct 93
FG - C	12 Oct 93	FG - F	08 Oct 93	FG - G	13 Oct 93	FG - G	13 Oct 93
FG - D	12 Oct 93	FG - B	11 Oct 93	FG - B	14 Oct 93	FG - B	14 Oct 93
FG - G	14 Oct 93	FG - D	11 Oct 93	FG - G	14 Oct 93	FG - B	14 Oct 93
FG - G	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93	FG - C	15 Oct 93

V Plant, %RCF=105%, %ΔRCF=0%



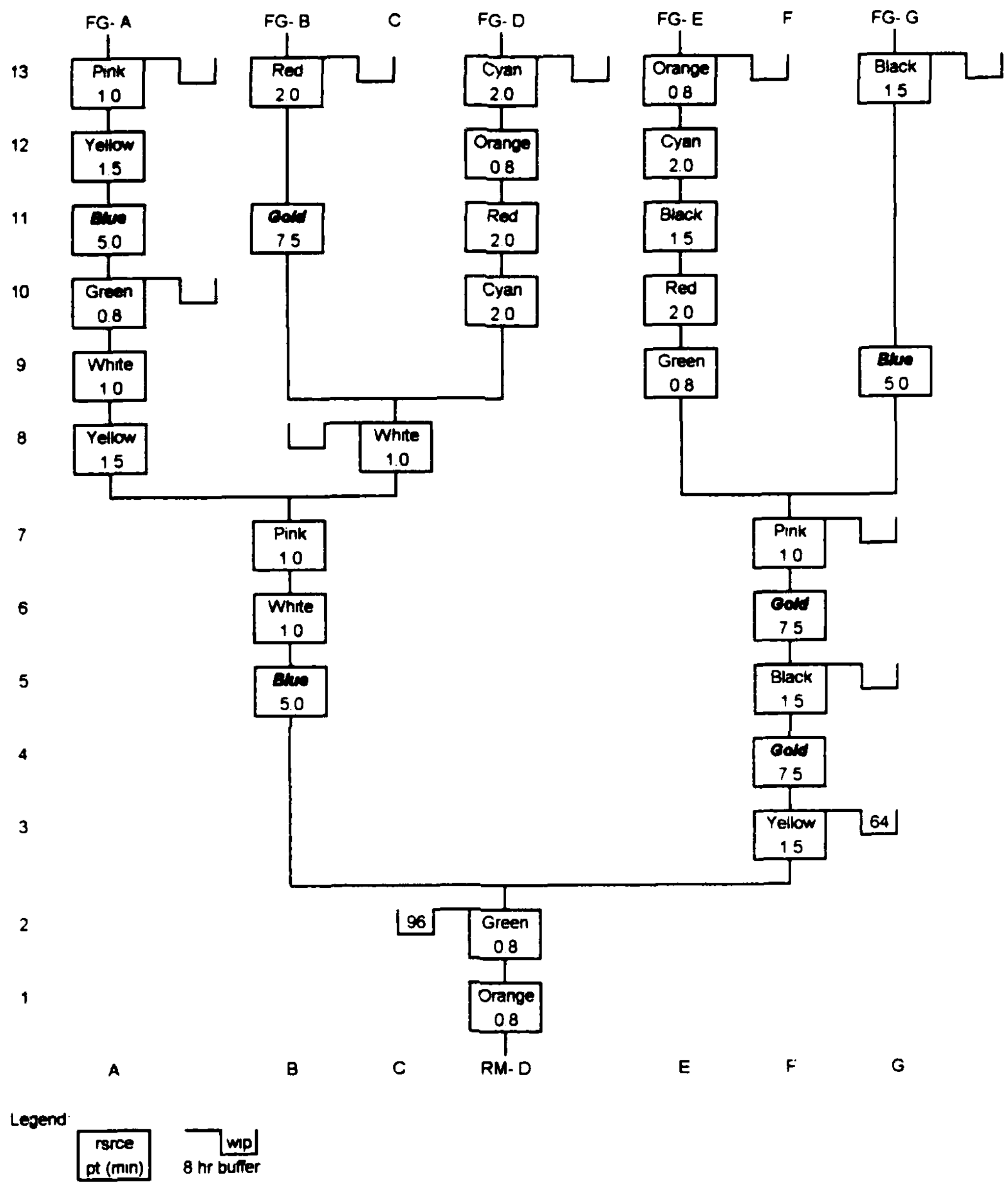
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	06 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	• 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	• 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=105%, %ΔRCF=25%



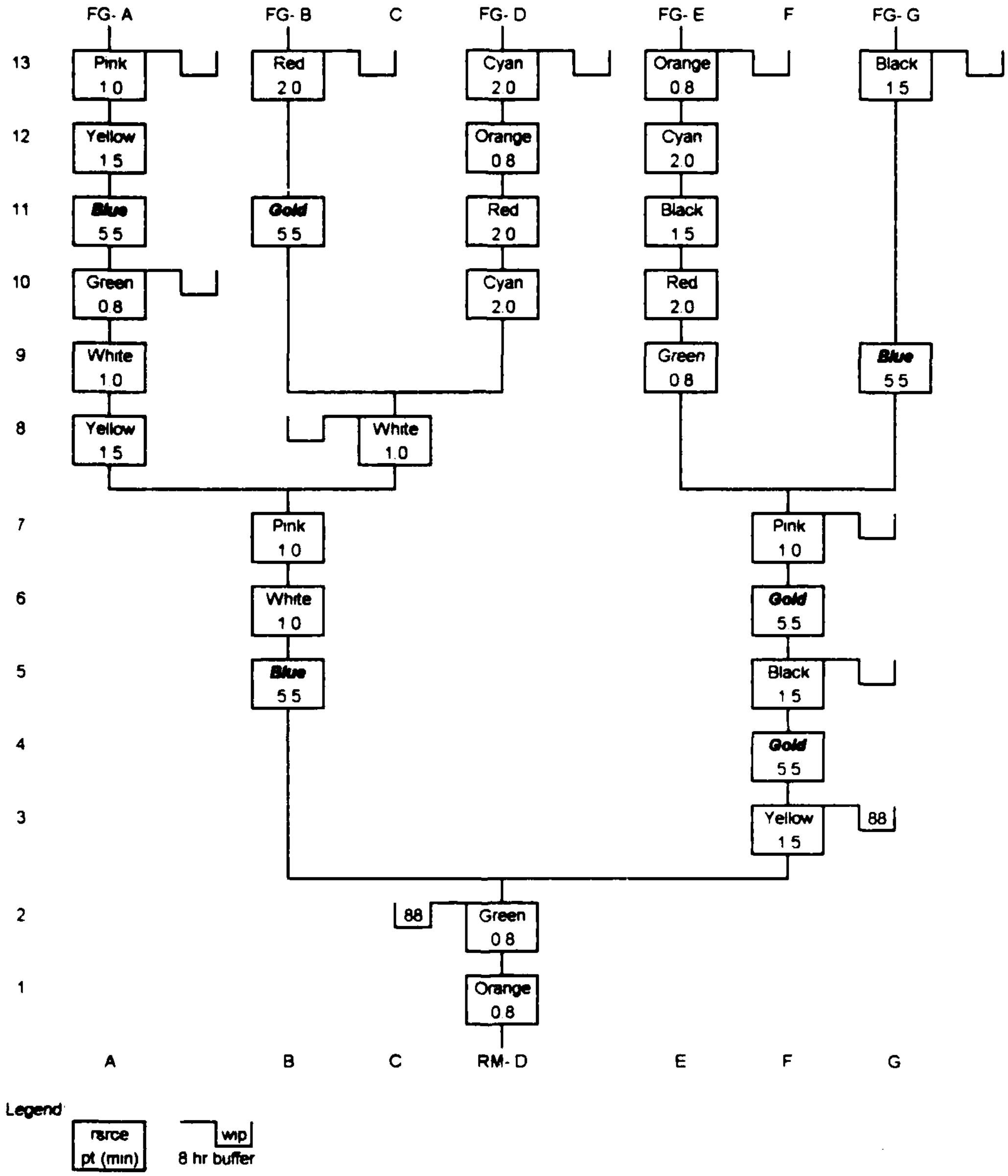
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=105%, %ΔRCF=50%



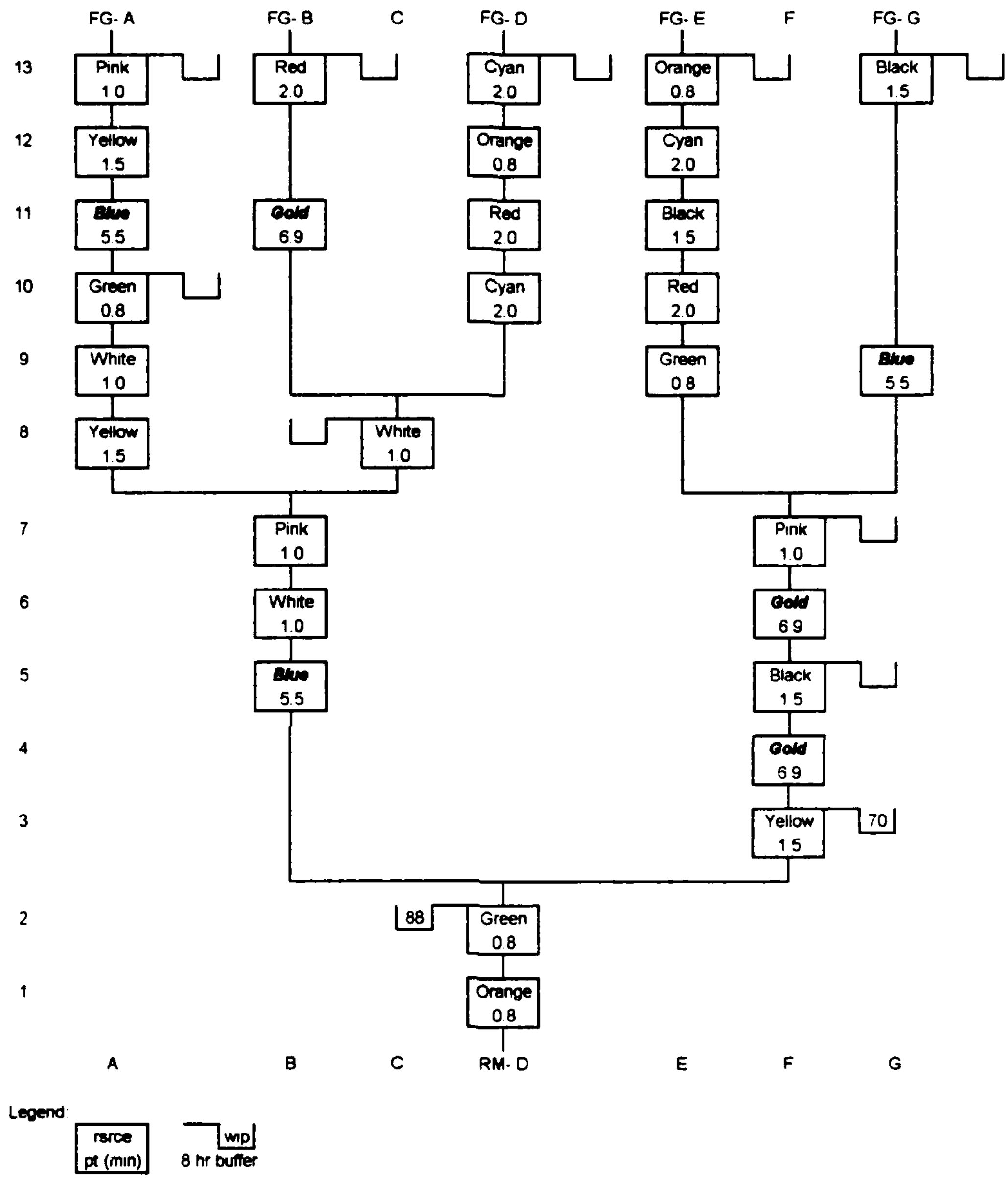
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	• 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	• 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=115%, %ΔRCF=0%



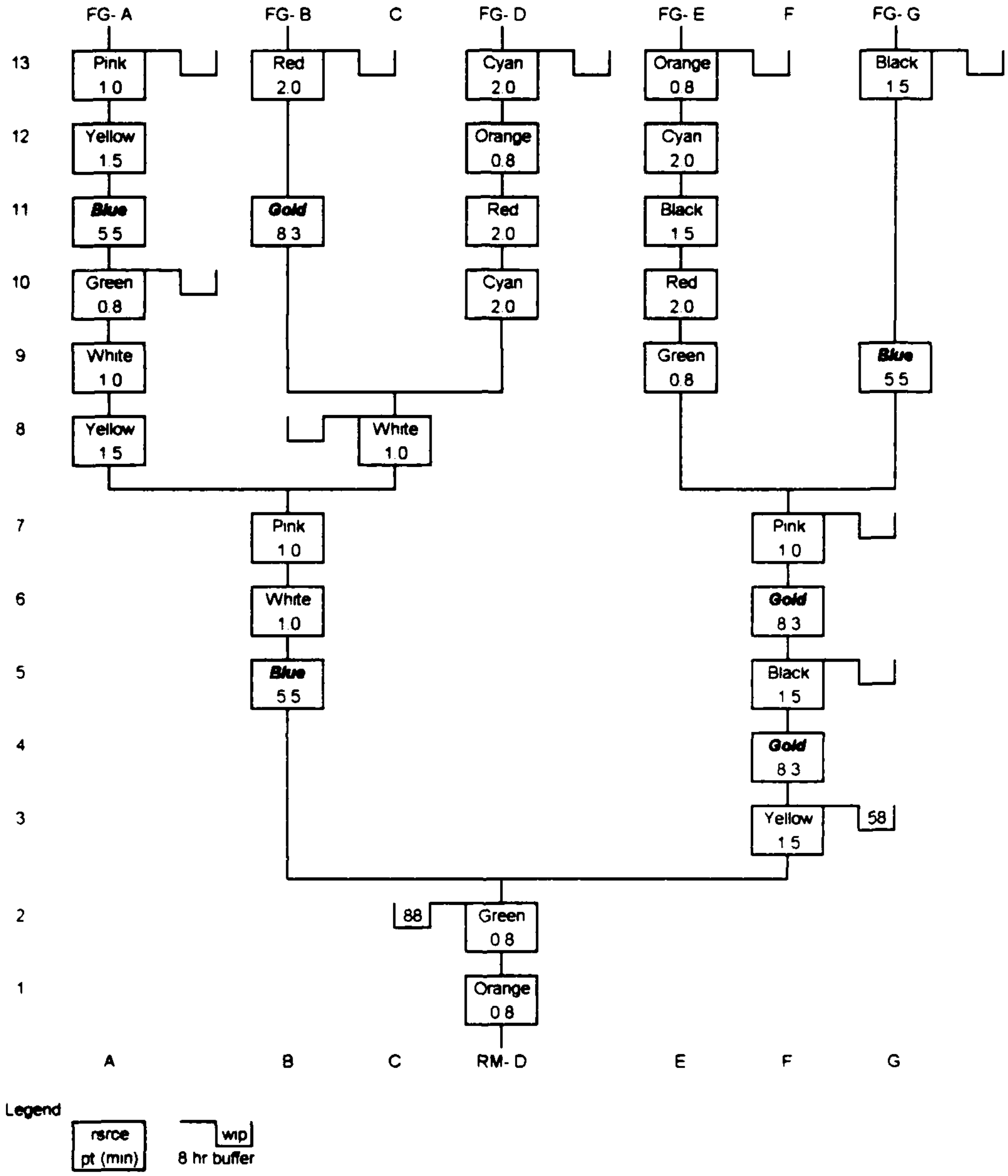
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=115%, %ΔRCF=25%



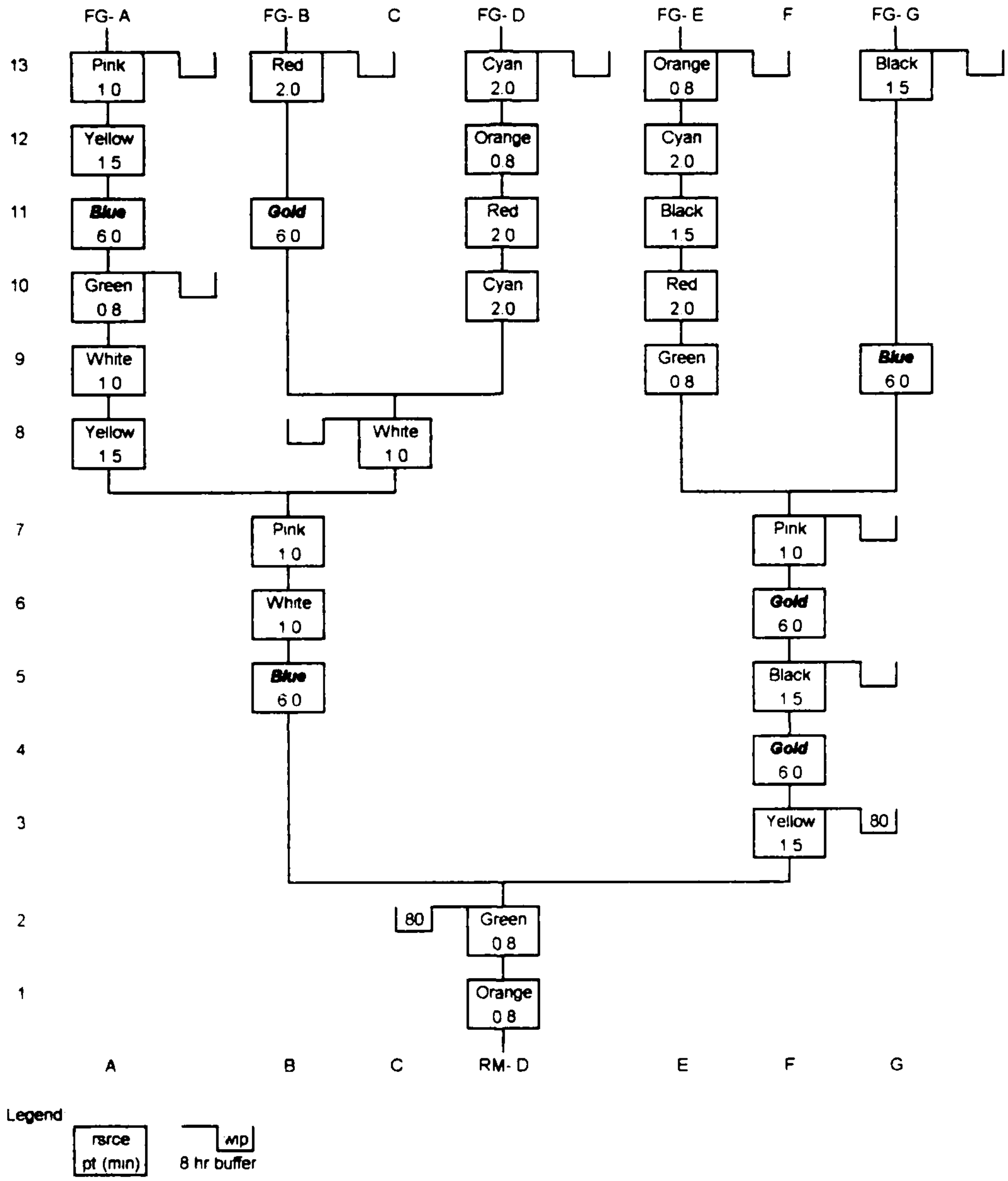
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	• 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	• 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=115%, %ΔRCF=50%



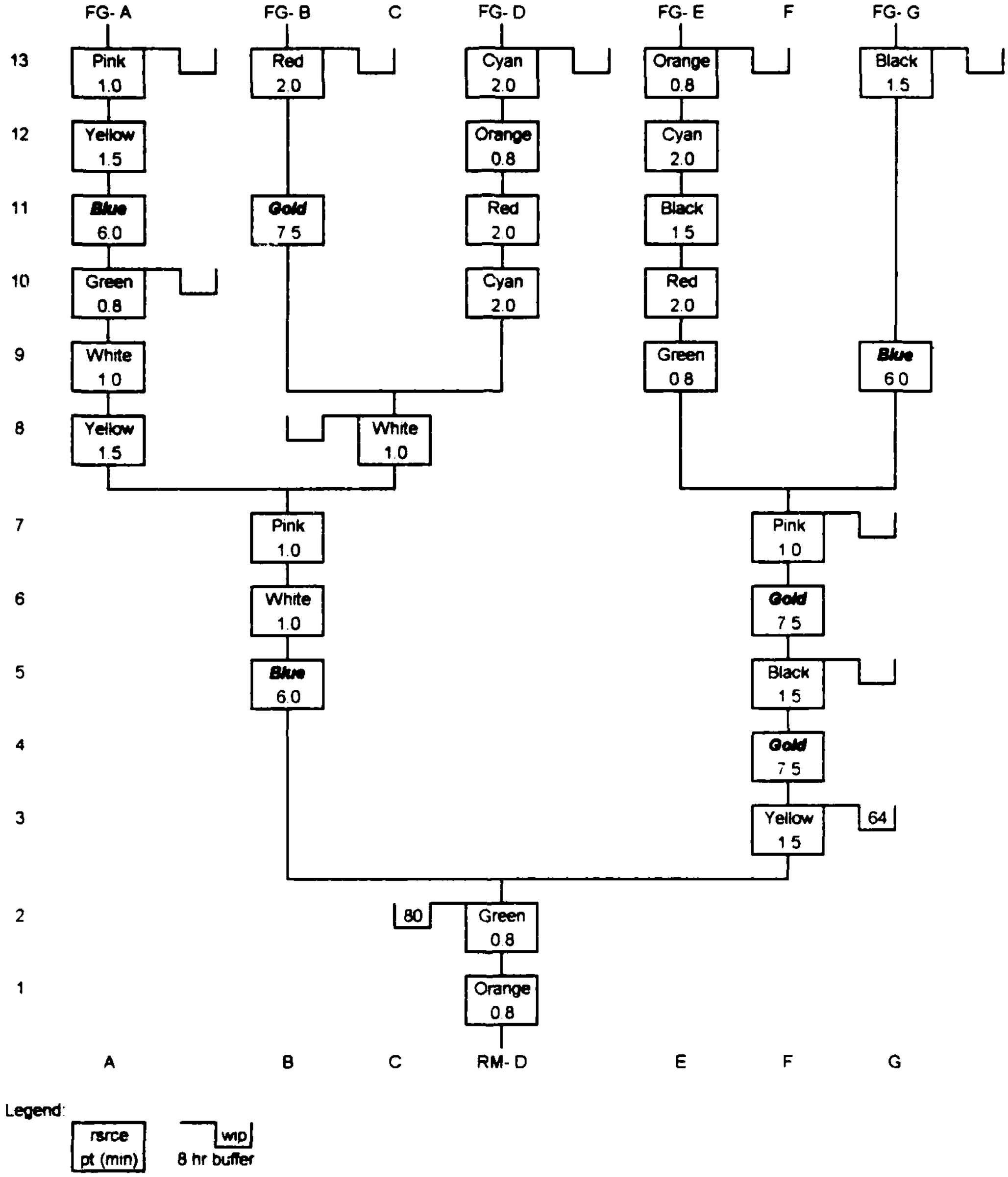
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	• 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	• 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=125%, %ΔRCF=0%



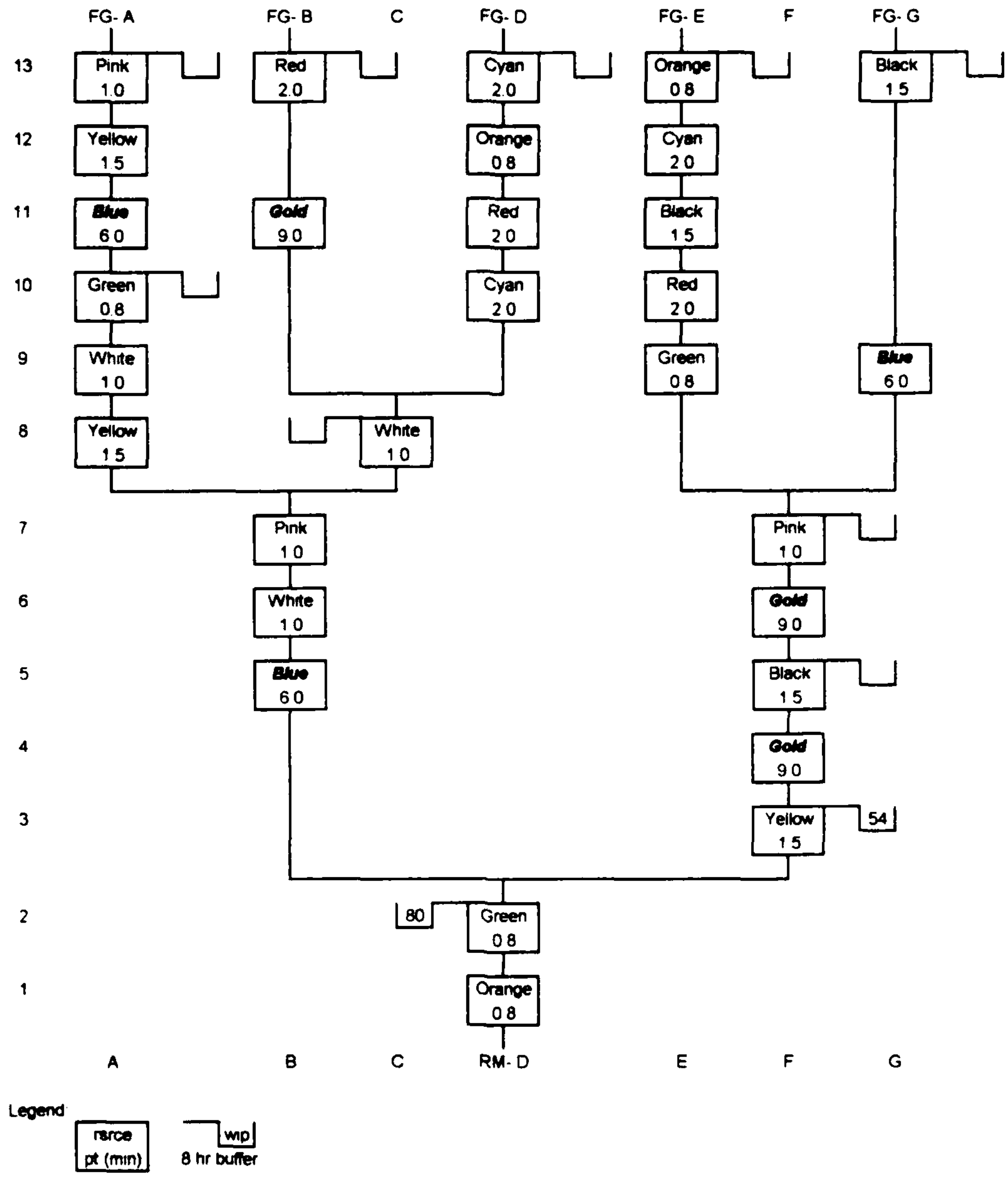
Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	• 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	• 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=125%, %ΔRCF=25%



Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	* 15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	* 15 Oct 93	FG - D	15 Oct 93

V Plant, %RCF=125%, %ΔRCF=50%



Job Orders Rep 1		Job Orders Rep 2		Job Orders Rep 3		Job Orders Rep 4	
Product Type	Due Date	Product Type	Due Date	Product Type	Due Date	Product Type	Due Date
FG - G	04 Oct 93	FG - E	04 Oct 93	FG - G	04 Oct 93	FG - A	04 Oct 93
FG - A	07 Oct 93	FG - A	06 Oct 93	FG - B	05 Oct 93	FG - A	05 Oct 93
FG - A	08 Oct 93	FG - B	06 Oct 93	FG - D	06 Oct 93	FG - G	05 Oct 93
FG - B	08 Oct 93	FG - D	07 Oct 93	FG - A	12 Oct 93	FG - B	06 Oct 93
FG - E	08 Oct 93	FG - G	08 Oct 93	FG - B	12 Oct 93	FG - E	06 Oct 93
FG - E	11 Oct 93	FG - B	12 Oct 93	FG - D	12 Oct 93	FG - G	06 Oct 93
FG - G	11 Oct 93	FG - D	12 Oct 93	FG - G	12 Oct 93	FG - B	07 Oct 93
FG - B	12 Oct 93	FG - G	12 Oct 93	FG - A	15 Oct 93	FG - E	07 Oct 93
FG - D	14 Oct 93	FG - A	13 Oct 93	FG - E	15 Oct 93	FG - D	08 Oct 93
FG - D	15 Oct 93	FG - E	15 Oct 93	FG - E	15 Oct 93	FG - D	15 Oct 93

Appendix D: Summary Data of DISASTER™ Output

A plant, %RCF blue constraint=105%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	22 / 24	4 / 5	9.1	25
rep 2	blue	yes / yes	10 / 9	3 / 3	11.1	0
rep 3	blue	yes / yes	14 / 13	3 / 2	7.7	50
rep 4	blue	yes / yes	20 / 19	4 / 4	5.3	0
average for gold / blue			16.5 / 16.25	3.5 / 3.5		

A plant, %RCF blue constraint=105%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	30 / 35	5 / 6	16.7	20
rep 2	gold	no / yes	16 / 20	5 / 5	25	0
rep 3	gold	no / yes	22 / 29	5 / 5	31.8	0
rep 4	gold	no / yes	29 / 32	5 / 8	10.3	60
average for gold / blue			24.25 / 29	5 / 6		

A plant, %RCF blue constraint=105%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	41 / 52	7 / 8	26.8	14.3
rep 2	gold	no / yes	24 / 37	7 / 8	54.2	14.3
rep 3	gold	no / yes	35 / 46	7 / 8	31.4	14.3
rep 4	gold	no / yes	41/ 51	7 / 10	24.3	42.9
average for gold / blue			35.25 / 46.5	7 / 8.5		

A plant, %RCF blue constraint=115%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	25 / 30	4 / 5	20	25
rep 2	blue	yes / yes	13 / 13	4 / 3	0	33.3
rep 3	blue	yes / yes	17 / 18	3 / 3	5.9	0
rep 4	blue	yes / yes	23 / 22	4 / 4	4.5	0
average for gold / blue			19.5 / 20.75	3.75 / 3.75		

A plant, %RCF blue constraint=115%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	35 / 48	6 / 7	37.1	16.6
rep 2	gold	no / yes	20 / 28	6 / 6	40	0
rep 3	gold	no / yes	28 / 53	6 / 8	89.3	33.3
rep 4	gold	no / yes	34 / 52	6 / 9	52.9	50
average for gold / blue			29.25 / 45.25	6 / 7.5		

A plant, %RCF blue constraint=115%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	48 / 60	9 / 9	25	0
rep 2	gold	no / yes	30 / 41	9 / 9	36.7	0
rep 3	gold	no / yes	43 / 55	9 / 9	27.9	0
rep 4	gold	no / yes	47 / 58	9 / 10	23.4	11.1
average for gold / blue			42 / 53.5	9 / 9.75		

A plant, %RCF blue constraint=125%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	29 / 35	4 / 6	20.7	50
rep 2	blue	yes / yes	16 / 18	5 / 4	12.5	25
rep 3	blue	yes / yes	23 / 23	4 / 4	0	0
rep 4	blue	yes / yes	29 / 29	5 / 5	0	0
average for gold / blue			24.25 / 26.25	4.5 / 4.75		

A plant, %RCF blue constraint=125%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	41 / 54	7 / 8	31.7	14.3
rep 2	gold	no / yes	24 / 33	7 / 8	37.5	14.3
rep 3	gold	no / yes	35 / 47	7 / 8	34.3	14.3
rep 4	gold	no / yes	41 / 53	7 / 9	29.3	28.6
average for gold / blue			35.25 / 46.75	7 / 8.5		

A plant, %RCF blue constraint=125%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	no / yes	55 / 71	10 / 12	29.1	20
rep 2	gold	no / yes	36 / 52	10 / 11	44.4	10
rep 3	gold	no / yes	50 / 77	10 / 12	54	20
rep 4	gold	no / yes	55 / 76	10 / 12	38.2	20
average for gold / blue			49 / 69	10 / 11.75		

T plant, %RCF blue constraint=105%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	25 / 22	8 / 4	13.6	100
rep 2	gold	yes / yes	37 / 35	6 / 8	5.7	33.3
rep 3	gold	yes / yes	9 / 14	3 / 3	55.5	0
rep 4	gold	yes / yes	10 / 18	4 / 6	80	50
average for gold / blue			20.25 / 22.25	5.25 / 5.25		

T plant, %RCF blue constraint=105%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	37 / 35	6 / 8	5.7	33.3
rep 2	gold	yes / yes	52 / 46	8 / 10	13	25
rep 3	gold	no / yes	19 / 39	5 / 12	105	140
rep 4	gold	yes / yes	20 / 40	6 / 10	100	66.7
average for gold / blue			32 / 40	6.25 / 10		

T plant, %RCF blue constraint=105%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	51 / 57	7 / 11	11.7	57.1
rep 2	gold	no / yes	65 / 63	10 / 11	3.2	10
rep 3	gold	no / yes	31 / 55	7 / 14	77.4	100
rep 4	gold	no / yes	30 / 52	7 / 12	73.3	71.4
average for gold / blue			44.25 / 56.75	7.75 / 9.25		

T plant, %RCF blue constraint=115%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	39 / 28	11 / 5	35.7	120
rep 2	gold	yes / yes	44 / 41	7 / 7	7.3	0
rep 3	blue	yes / yes	14 / 16	4 / 4	14.3	0
rep 4	gold	yes / yes	14 / 22	5 / 7	57.1	40
average for gold / blue			27.75 / 26.75	6.75 / 5.75		

T plant, %RCF blue constraint=115%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	46 / 42	7 / 9	9.5	28.6
rep 2	gold	no / yes	60 / 57	9 / 12	5.2	33.3
rep 3	gold	no / yes	26 / '1	6 / 13	57.7	116.7
rep 4	gold	no / yes	26 / 48	6 / 11	84.6	83.3
average for gold / blue			39.5 / 47	7 / 11.25		

T plant, %RCF blue constraint=115%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	61 / 67	9 / 13	9.8	44.4
rep 2	gold	no / yes	77 / 73	12 / 13	5.5	8.3
rep 3	gold	no / yes	43 / 60	9 / 16	39.5	77.7
rep 4	gold	no / yes	39 / 61	9 / 14	56.4	55.5
average for gold / blue			55 / 65.25	9.75 / 14		

T plant, %RCF blue constraint=125%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	blue	yes / yes	45 / 32	12 / 6	40.6	100
rep 2	gold	yes / yes	48 / 45	8 / 10	6.7	25
rep 3	gold	yes / yes	19 / 20	5 / 5	5.3	0
rep 4	gold	yes / yes	18 / 25	6 / 8	38.9	33.3
average for gold / blue			32.5 / 30.5	7.75 / 7.25		

T plant, %RCF blue constraint=125%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	52 / 52	7 / 11	0	57.1
rep 2	gold	yes / yes	72 / 61	11 / 12	18	9.1
rep 3	gold	no / yes	31 / 31	7 / 7	0	0
rep 4	gold	no / yes	30 / 53	7 / 12	76.7	71.4
average for gold / blue			46.25 / 49.25	8 / 10.5		

T plant, %RCF blue constraint=125%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	69 / 73	10 / 14	5.8	40
rep 2	gold	no / yes	80 / 80	13 / 14	0	7.1
rep 3	gold	no / yes	48 / 67	10 / 17	39.6	70
rep 4	gold	no / yes	45 / 69	10 / 15	53.3	50
average for gold / blue			60.5 / 72.25	10.75 / 15		

V plant, %RCF blue constraint=105%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	26 / 27	5 / 6	3.8	20
rep 2	gold	yes / yes	25 / 25	4 / 4	0	0
rep 3	gold	yes / yes	18 / 19	3 / 4	5.5	33.3
rep 4	gold	yes / yes	50 / 47	8 / 8	6.4	0
average for gold / blue			29.75 / 29.5	5 / 5.5		

V plant, %RCF blue constraint=105%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	36 / 38	8 / 9	5.5	12.5
rep 2	gold	yes / yes	29 / 39	6 / 11	34.5	120
rep 3	gold	yes / yes	21 / 22	5 / 5	4.7	0
rep 4	gold	yes / yes	64 / 59	11 / 11	8.5	0
average for gold / blue			37.5 / 39.5	7.5 / 9		

V plant, %RCF blue constraint=105%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	43 / 42	10 / 11	2.4	10
rep 2	gold	yes / yes	34 / 43	8 / 13	2.6	62.5
rep 3	gold	yes / yes	25 / 27	7 / 7	8	0
rep 4	gold	yes / yes	65 / 63	13 / 13	3.1	0
average for gold / blue			41.75 / 43.75	9.5 / 11		

V plant, %RCF blue constraint=115%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	31 / 34	6 / 7	9.7	16.7
rep 2	gold	yes / yes	30 / 30	5 / 5	0	0
rep 3	gold	yes / yes	23 / 24	4 / 4	4.3	0
rep 4	gold	yes / yes	55 / 53	9 / 9	3.8	0
average for gold / blue			34.75 / 35.25	6 / 6.25		

V plant, %RCF blue constraint=115%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	46 / 44	9 / 10	4.5	11.1
rep 2	gold	yes / yes	35 / 42	7 / 13	20	85.7
rep 3	gold	yes / yes	34 / 27	6 / 6	25.9	0
rep 4	gold	yes / yes	61 / 66	12 / 12	8.2	0
average for gold / blue			44 / 44.75	8.5 / 10.25		

V plant, %RCF blue constraint=115%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	49 / 50	12 / 13	2	8.3
rep 2	gold	yes / yes	43 / 51	9 / 14	18.6	55.5
rep 3	gold	yes / yes	32 / 37	9 / 9	15.6	0
rep 4	gold	yes / yes	72 / 71	15 / 15	1.4	0
average for gold / blue			49 / 52.25	11.25 / 12.7		

V plant, %RCF blue constraint=125%, %Delta RCF=0%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	41 / 40	7 / 8	2.5	14.3
rep 2	blue	yes / yes	34 / 38	6 / 6	11.7	0
rep 3	gold	yes / yes	31 / 29	5 / 5	6.9	0
rep 4	gold	yes / yes	62 / 60	10 / 10	3.3	0
average for gold / blue			42 / 41.75	7 / 7.25		

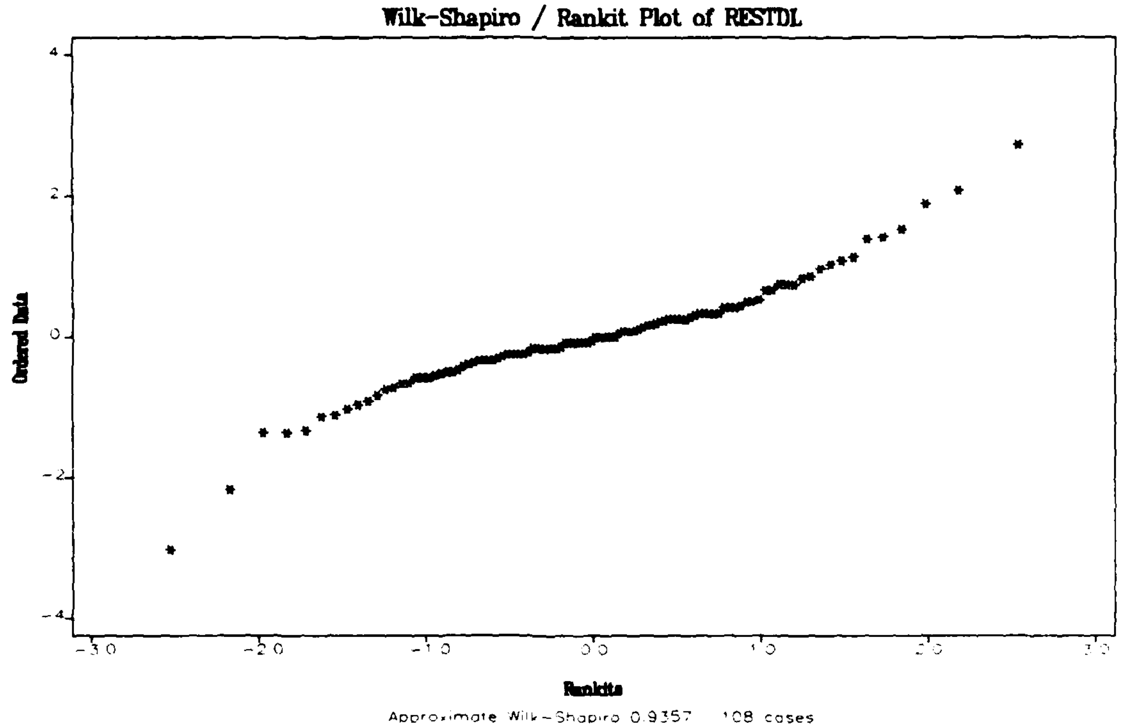
V plant, %RCF blue constraint=125%, %Delta RCF=25%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	46 / 52	10 / 10	13	0
rep 2	gold	yes / yes	41 / 50	8 / 13	21.9	62.5
rep 3	gold	yes / yes	38 / 32	7 / 7	18.75	0
rep 4	gold	yes / yes	69 / 75	13 / 14	8.7	7.7
average for gold / blue			48.5 / 52.25	9.5 / 11		

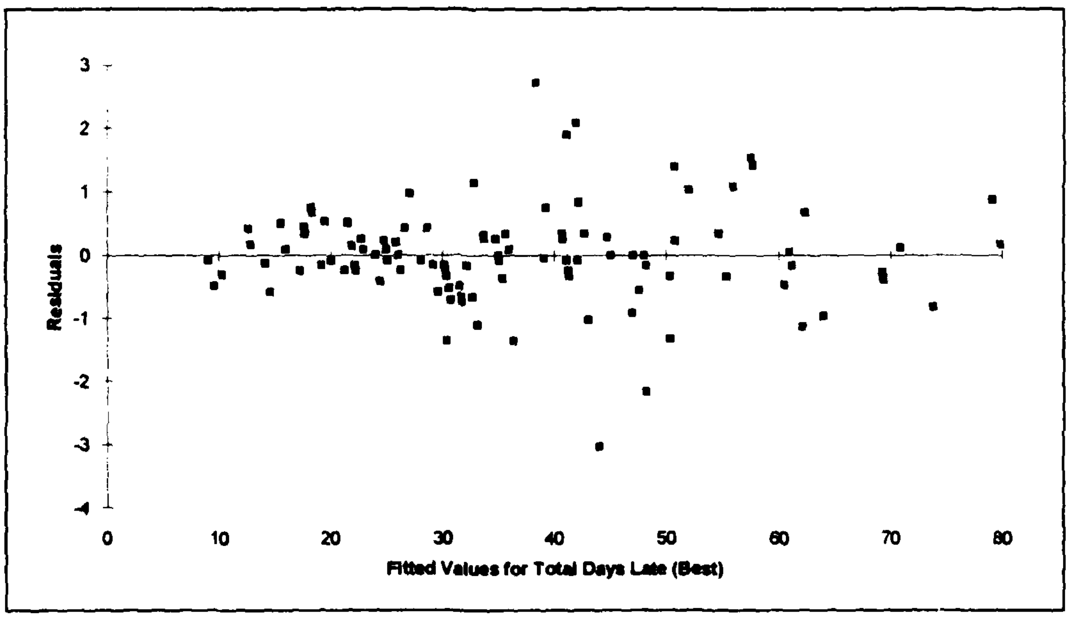
V plant, %RCF blue constraint=125%, %Delta RCF=50%

	constraint DISASTER first chose	dual interactive constraints? gold 1st / blue 1st	total number of days late gold 1st / blue 1st	maximum tardiness gold 1st / blue 1st	% delta for total days late	% delta for max tardiness
rep 1	gold	yes / yes	60 / 59	13 / 14	1.7	7.7
rep 2	gold	yes / yes	41 / 61	10 / 16	48.8	60
rep 3	gold	yes / yes	40 / 40	10 / 10	0	0
rep 4	gold	yes / yes	81 / 80	16 / 16	1.25	0
average for gold / blue			55.5 / 60	12.25 / 14		

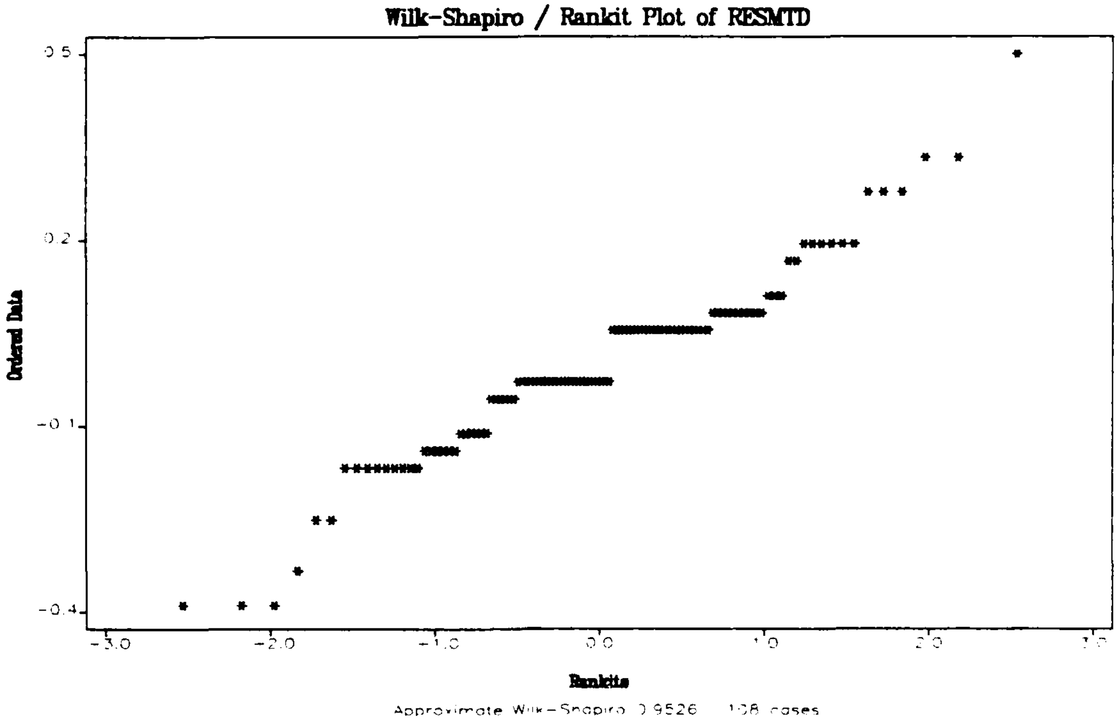
Appendix E: Assumptions of ANOVA Model for TDL_{best} and MTD_{best}



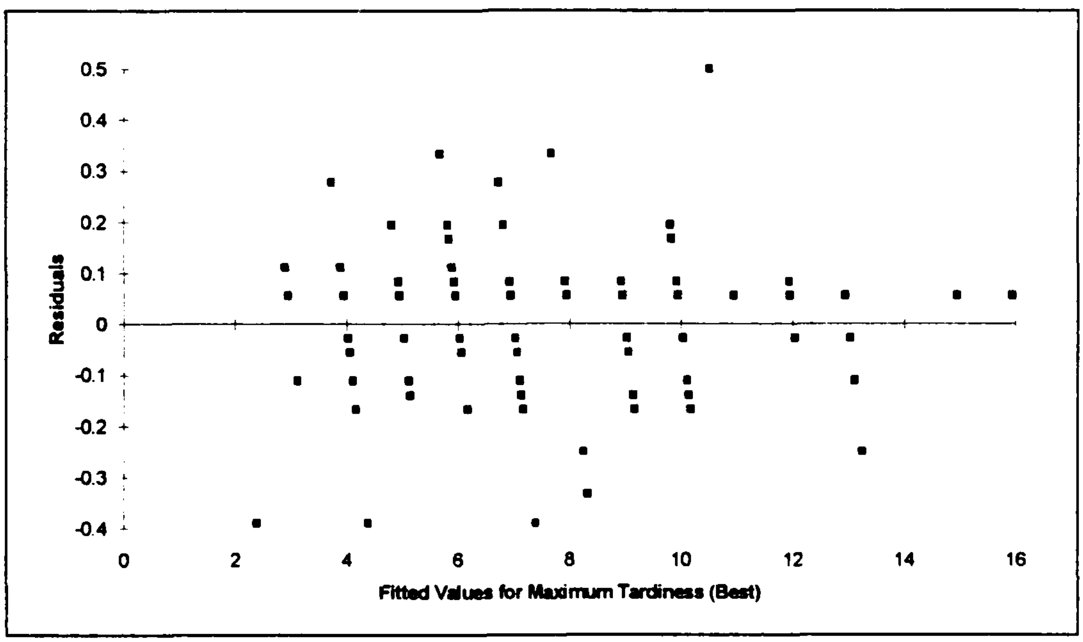
Normality Assessment Plot for TDL_{best}



Constant Variance Assessment Scatterplot for TDL_{best}



Normality Assessment Plot for MTD_{best}



Constant Variance Assessment Scatterplot for MTD_{best}

Appendix F: ANOVA Results for TDL_{best}

STATISTIX 4.0 TDL, 08/09/93, 19:40

ANALYSIS OF VARIANCE TABLE FOR BESTTDL

SOURCE	DF	SS	MS	F	P
PLANT (A)	2	2288.22	1144.11	0.79	0.4848
REP (B)					
A*B	9	13110.0	1456.66		
PRCF (C)	2	2666.00	1333.00	398.42	0.0000
A*C	4	24.4444	6.11111	1.83	0.1677
A*B*C	18	60.2222	3.34567		
PDELRCF (D)	2	8400.16	4200.08	300.34	0.0000
A*D	4	714.777	178.694	12.78	0.0000
A*B*D	18	251.722	13.9845		
C*D	4	79.1666	19.7916	11.08	0.0000
A*C*D	8	17.8888	2.23611	1.25	0.2984
A*B*C*D	36	64.2777	1.78549		
TOTAL	107	27676.9			
GRAND AVERAGE	1	1.450E+05			

STATISTIX 4.0 TDL, 08/09/93, 19:41

TUKEY (HSD) PAIRWISE COMPARISONS OF MEANS OF BESTTDL BY PRCF

PRCF	MEAN	HOMOGENEOUS GROUPS
125	42.638	I
115	36.805	.. I
105	30.472	 I

ALL 3 MEANS ARE SIGNIFICANTLY DIFFERENT FROM ONE ANOTHER.

CRITICAL Q VALUE	3.611	REJECTION LEVEL	0.050
CRITICAL VALUE FOR COMPARISON	1.1007		
STANDARD ERROR FOR COMPARISON	0.4311		

ERROR TERM USED: PLANT*REP*PRCF, 18 DF

STATISTIX 4.0 TDL, 08/09/93, 19:42

TUKEY (HSD) PAIRWISE COMPARISONS OF MEANS OF BESTTDL BY PDELRCF

PDELRCF	MEAN	HOMOGENEOUS GROUPS
50	47.694	I
25	36.111	.. I
0	26.111	 I

ALL 3 MEANS ARE SIGNIFICANTLY DIFFERENT FROM ONE ANOTHER.

CRITICAL Q VALUE	3.611	REJECTION LEVEL	0.050
CRITICAL VALUE FOR COMPARISON	2.2504		
STANDARD ERROR FOR COMPARISON	0.8814		

ERROR TERM USED: PLANT*REP*PDELRCF, 18 DF

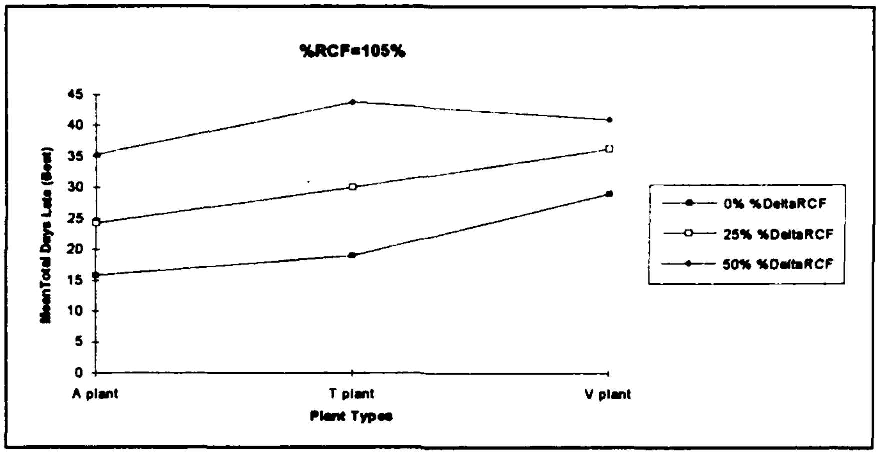
Number of observations in data set = 108
Grand Mean BESTTDL = 36.639

Level of PLANT	Level of PCRCF	N	TDL Mean	TDL SD
A	H	12	36.1666667	12.7195864
A	L	12	25.0833333	10.3963134
A	M	12	30.1666667	11.5745279
T	H	12	44.1666667	19.3100696
T	L	12	30.9166667	16.3843514
T	M	12	38.6666667	18.3418713
V	H	12	47.5833333	15.8714056
V	L	12	35.4166667	14.6315868
V	M	12	41.5833333	14.6935876

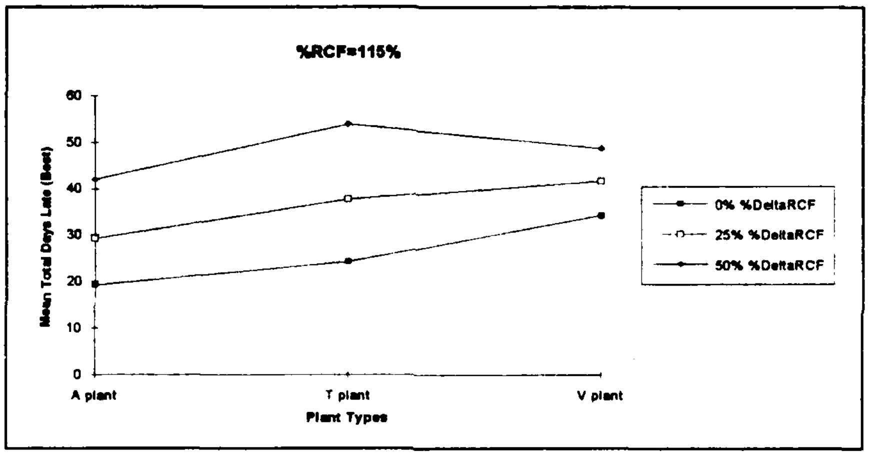
Level of PLANT	Level of PCDRCF	N	TDL Mean	TDL SD
A	H	12	42.0833333	9.6243851
A	N	12	19.7500000	6.3835727
A	L	12	29.5833333	8.0165548
T	H	12	52.7500000	16.3769517
T	N	12	23.9166667	12.1240432
T	L	12	37.0833333	14.3048519
V	H	12	48.2500000	16.6631057
V	N	12	34.6666667	12.8228017
V	L	12	41.6666667	14.8283104

Level of PCRCF	Level of PCDRCF	N	TDL Mean	TDL SD
H	H	12	54.8333333	14.8252446
H	N	12	31.1666667	12.5830574
H	L	12	41.9166667	13.3038500
L	H	12	40.0000000	13.1702143
L	N	12	21.2500000	11.2825287
L	L	12	30.1666667	12.5106016
M	H	12	48.2500000	13.6855930
M	N	12	25.9166667	11.9198714
M	L	12	36.2500000	12.6930547

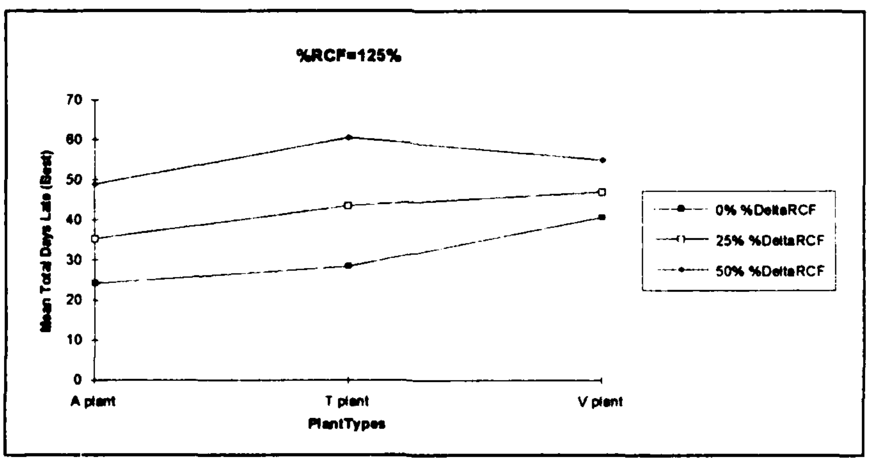
Level of PLANT	Level of PCRCF	Level of PCDRCF	N	TDL Mean	TDL SD
A	H	H	4	49.0000000	8.9814624
A	H	N	4	24.2500000	6.1846584
A	H	L	4	35.2500000	8.0156098
A	L	H	4	35.2500000	8.0156098
A	L	N	4	15.7500000	5.8523500
A	L	L	4	24.2500000	6.5510813
A	M	H	4	42.0000000	8.2865353
A	M	N	4	19.2500000	5.3150729
A	M	L	4	29.2500000	6.8980674
T	H	H	4	60.5000000	16.8226038
T	H	N	4	28.5000000	12.7148207
T	H	L	4	43.5000000	15.4596248
T	L	H	4	43.7500000	16.0701587
T	L	N	4	19.0000000	12.1928941
T	L	L	4	30.0000000	12.9357386
T	M	H	4	54.0000000	15.8745079
T	M	N	4	24.2500000	12.9711218
T	M	L	4	37.7500000	14.8856754
V	H	H	4	55.0000000	18.8148877
V	H	N	4	40.7500000	13.5984068
V	H	L	4	47.0000000	15.7691682
V	L	H	4	41.0000000	16.2275486
V	L	N	4	29.0000000	12.5166556
V	L	L	4	36.2500000	16.3579746
V	M	H	4	48.7500000	16.4189931
V	M	N	4	34.2500000	12.9967945
V	M	L	4	41.7500000	14.5916643



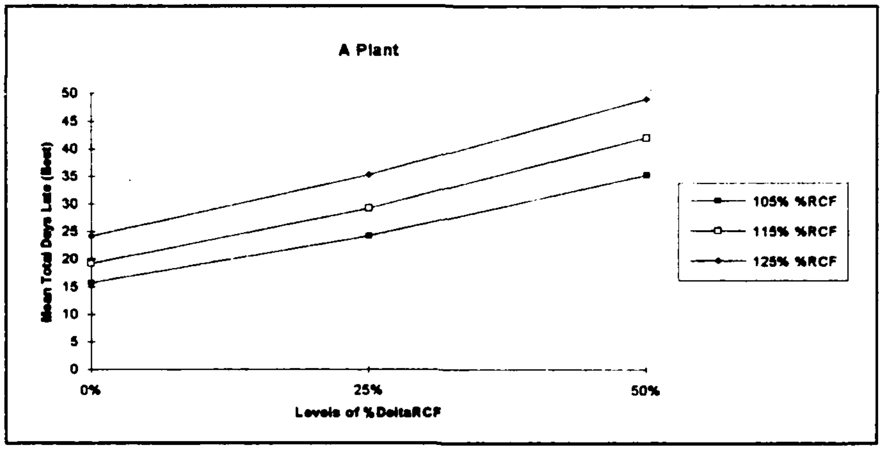
(Plant Type * %ΔRCF) for %RCF = 105%



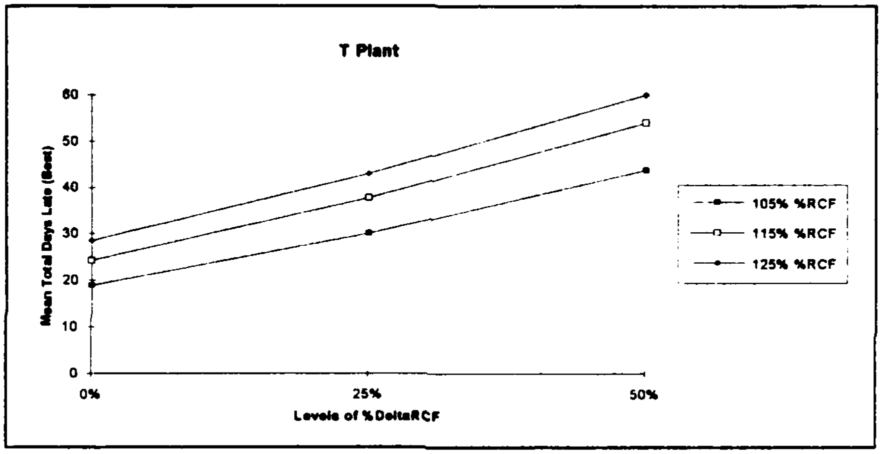
(Plant Type * %ΔRCF) for %RCF = 115%



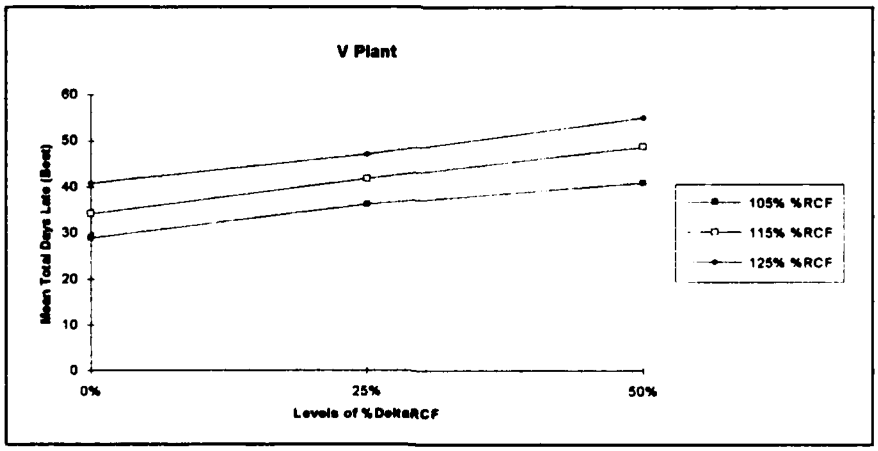
(Plant Type * %ΔRCF) for %RCF = 125%



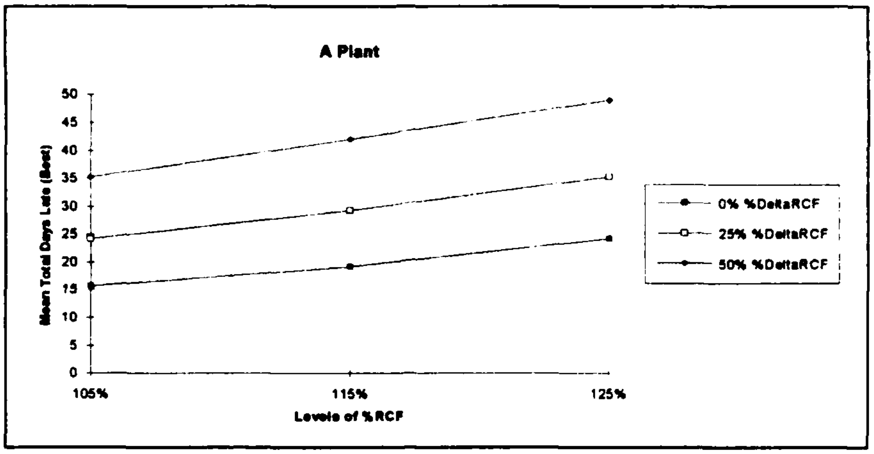
(%RCF * %ΔRCF) for A Plant



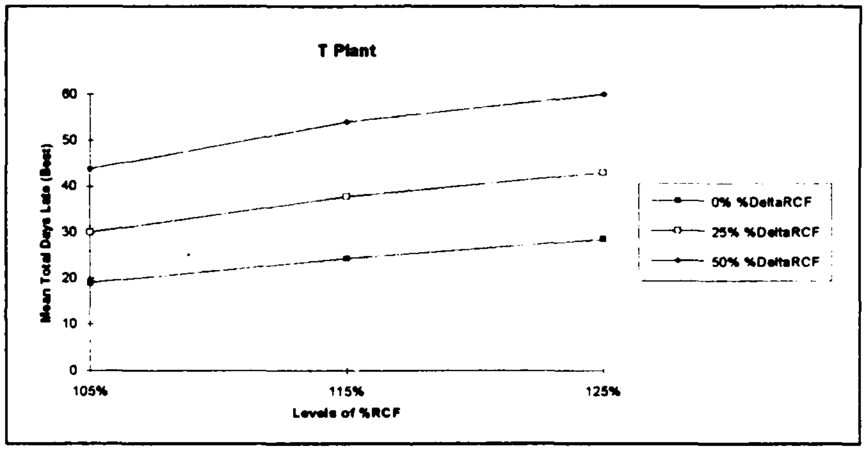
(%RCF * %ΔRCF) for T Plant



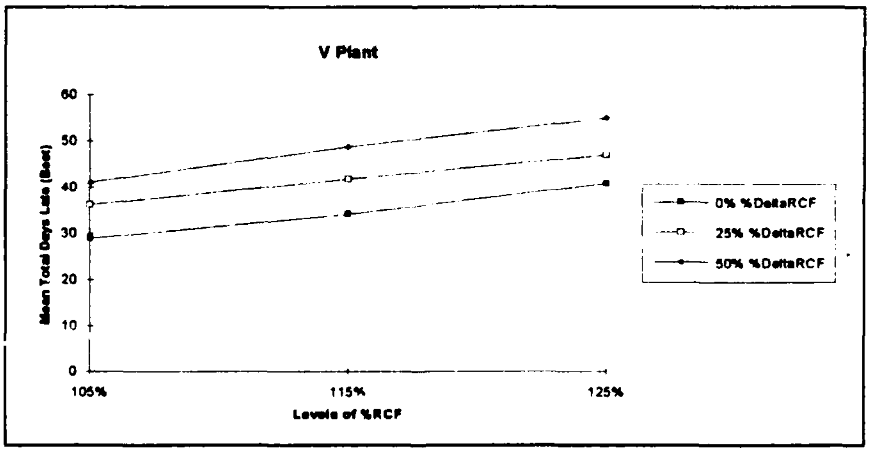
(%RCF * %ΔRCF) for V Plant



(%ΔRCF * %RCF) for A Plant



(%ΔRCF * %RCF) for T Plant



(%ΔRCF * %RCF) for V Plant

Appendix G: ANOVA Results for MTD_{best}

STATISTIX 4.0 MTD, 08/09/93,
20:42

ANALYSIS OF VARIANCE TABLE FOR BESTMTD

SOURCE	DF	SS	MS	F	P
PLANT (A)	2	102.796	51.3981	2.04	0.1855
REP (B)					
A*B	9	226.416	25.1574		
PRCF (C)	2	84.7962	42.3981	654.14	0.0000
A*C	4	0.25925	0.06481	1.00	0.4332
A*B*C	18	1.16666	0.06481		
PDELRCF (D)	2	401.851	200.925	493.18	0.0000
A*D	4	3.03703	0.75925	1.86	0.1608
A*B*D	18	7.33333	0.40740		
C*D	4	6.70370	1.67592	25.86	0.0000
A*C*D	8	1.40740	0.17592	2.71	0.0189
A*B*C*D	36	2.33333	0.06481		
TOTAL	107	838.101			
GRAND AVERAGE	1	5734.89			

STATISTIX 4.0 MTD, 08/09/93,
20:43

TUKEY (HSD) PAIRWISE COMPARISONS OF MEANS OF BESTMTD BY PRCF

PRCF	MEAN	HOMOGENEOUS GROUPS
125	8.3333	I
115	7.3611	.. I
105	6.1666	 I

ALL 3 MEANS ARE SIGNIFICANTLY DIFFERENT FROM ONE ANOTHER.

CRITICAL Q VALUE	3.611	REJECTION LEVEL	0.050
CRITICAL VALUE FOR COMPARISON	0.1532		
STANDARD ERROR FOR COMPARISON	0.0600		

ERROR TERM USED: PLANT*REP*PRCF, 18 DF

STATISTIX 4.0 MTD, 08/09/93,
20:43

TUKEY (HSD) PAIRWISE COMPARISONS OF MEANS OF BESTMTD BY PDELRCF

PDELRCF	MEAN	HOMOGENEOUS GROUPS
50	9.6944	I
25	7.1944	.. I
0	4.9722	 I

ALL 3 MEANS ARE SIGNIFICANTLY DIFFERENT FROM ONE ANOTHER.

CRITICAL Q VALUE	3.611	REJECTION LEVEL	0.050
CRITICAL VALUE FOR COMPARISON	0.3841		
STANDARD ERROR FOR COMPARISON	0.1504		

ERROR TERM USED: PLANT*REP*PDELRCF, 18 DF

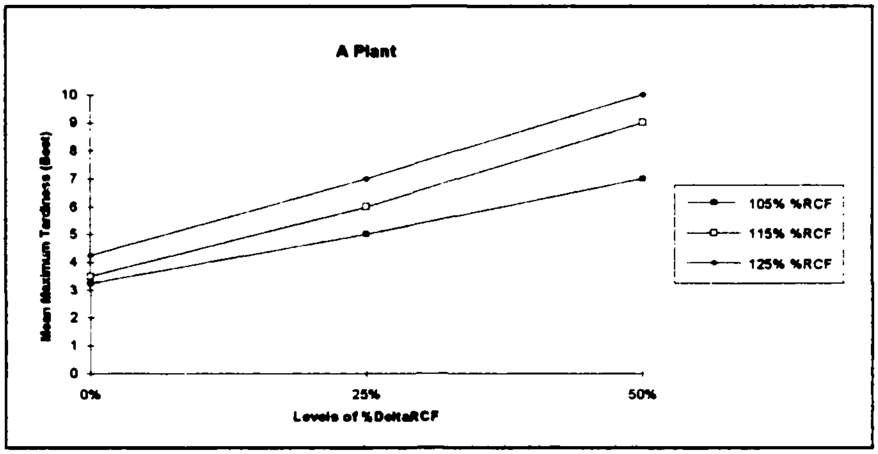
Number of observations in data set = 108
Grand Mean BESTMTD = 7.2870

Level of PLANT	Level of PCRCF	N	MDL Mean	MDL SD
A	H	12	7.08333333	2.46644143
A	L	12	5.08333333	1.67648622
A	M	12	6.16666667	2.36771210
T	H	12	8.33333333	2.42462118
T	L	12	6.08333333	1.92865159
T	M	12	7.33333333	2.30940108
V	H	12	9.58333333	3.23217724
V	L	12	7.33333333	2.96443566
V	M	12	8.58333333	3.23217724

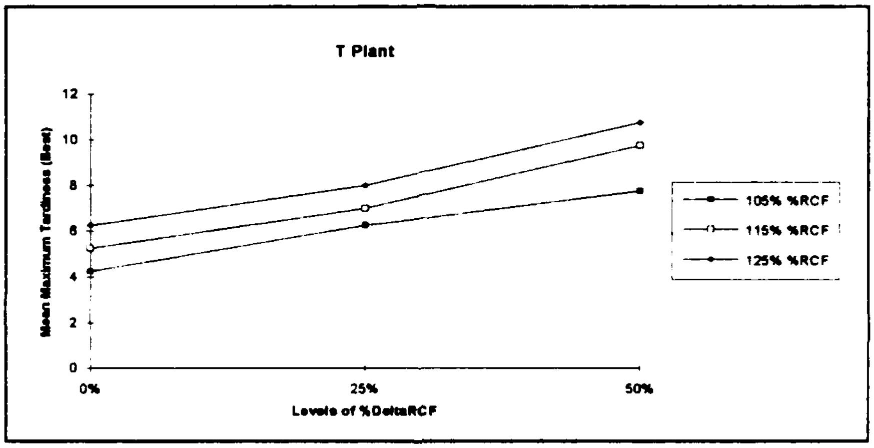
Level of PLANT	Level of PCDRCF	N	MDL Mean	MDL SD
A	H	12	8.6666667	1.30267789
A	N	12	3.6666667	0.77849894
A	L	12	6.0000000	0.85280287
T	H	12	9.4166667	1.88092498
T	N	12	5.2500000	1.42222617
T	L	12	7.0833333	1.62135372
V	H	12	11.0000000	2.79610118
V	N	12	6.0000000	2.13200716
V	L	12	8.5000000	2.54057975

Level of PCRCF	Level of PCDRCF	N	MDL Mean	MDL SD
H	H	12	11.0000000	1.95401684
H	N	12	5.8333333	1.80067327
H	L	12	8.1666667	2.03752672
L	H	12	8.0833333	1.92865159
L	N	12	4.1666667	1.58592292
L	L	12	6.2500000	1.86474468
M	H	12	10.0000000	1.95401684
M	N	12	4.9166667	1.72986249
M	L	12	7.1666667	1.89896303

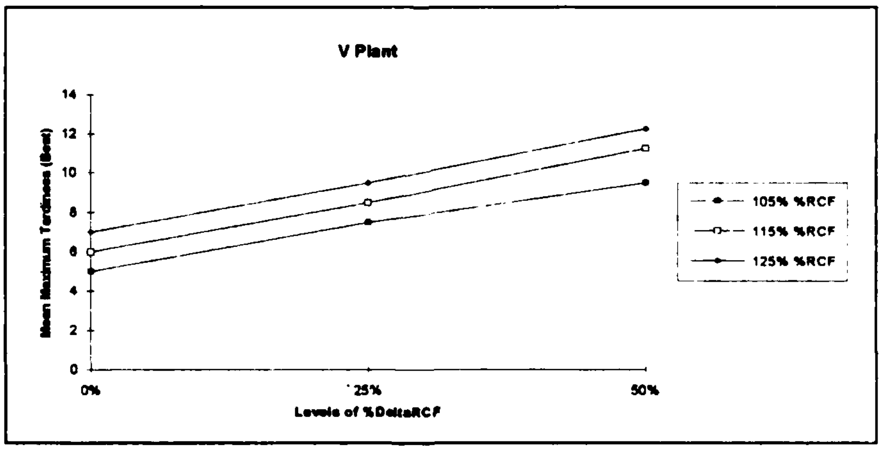
Level of PLANT	Level of PCRCF	Level of PCDRCF	N	-------------MDL-------------	
				Mean	SD
A	H	H	4	10.0000000	0.00000000
A	H	N	4	4.2500000	0.50000000
A	H	L	4	7.0000000	0.00000000
A	L	H	4	7.0000000	0.00000000
A	L	N	4	3.2500000	0.95742711
A	L	L	4	5.0000000	0.00000000
A	M	H	4	9.0000000	0.00000000
A	M	N	4	3.5000000	0.57735027
A	M	L	4	6.0000000	0.00000000
T	H	H	4	10.7500000	1.50000000
T	H	N	4	6.2500000	1.25830574
T	H	L	4	8.0000000	2.00000000
T	L	H	4	7.7500000	1.50000000
T	L	N	4	4.2500000	1.25830574
T	L	L	4	6.2500000	1.25830574
T	M	H	4	9.7500000	1.50000000
T	M	N	4	5.2500000	1.25830574
T	M	L	4	7.0000000	1.41421356
V	H	H	4	12.2500000	2.87228132
V	H	N	4	7.0000000	2.16024690
V	H	L	4	9.5000000	2.64575131
V	L	H	4	9.5000000	2.64575131
V	L	N	4	5.0000000	2.16024690
V	L	L	4	7.5000000	2.64575131
V	M	H	4	11.2500000	2.87228132
V	M	N	4	6.0000000	2.16024690
V	M	L	4	8.5000000	2.64575131



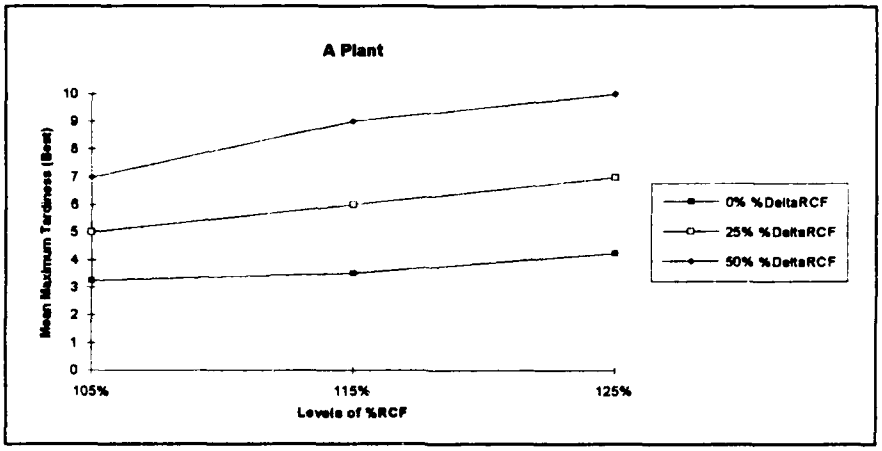
(Plant Type * %RCF * %ΔRCF) part 1a
(%ΔRCF * %RCF) for A Plant



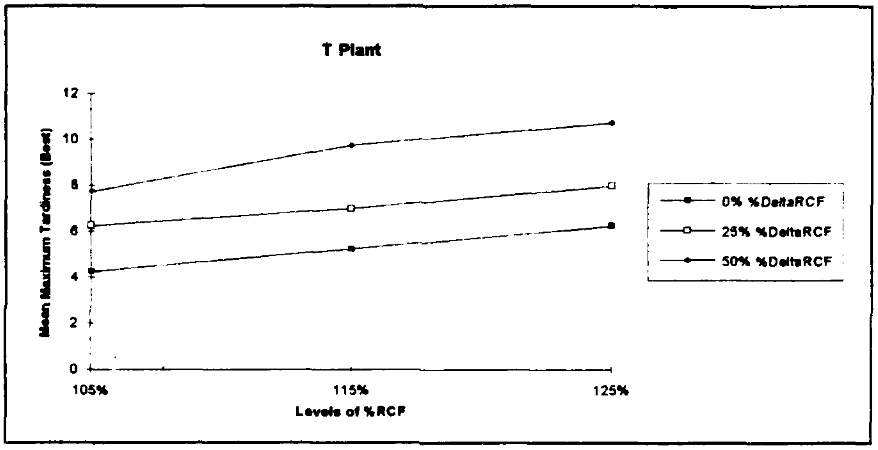
(Plant Type * %RCF * %ΔRCF) part 1b
(%ΔRCF * %RCF) for T Plant



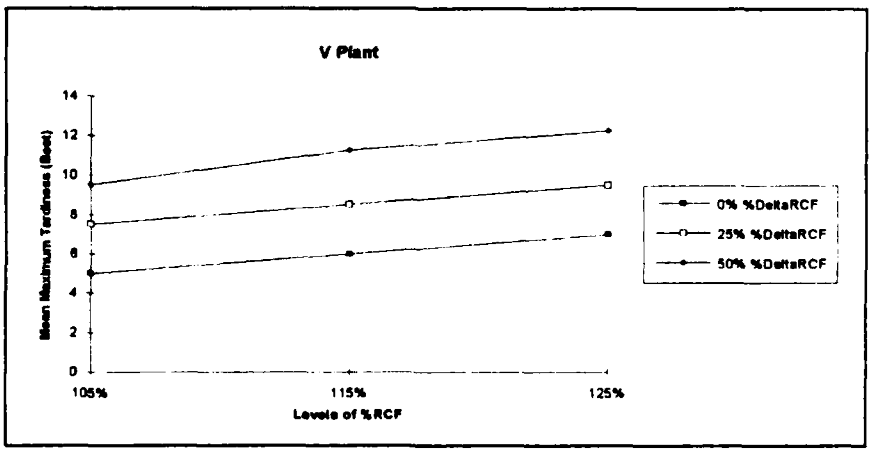
(Plant Type * %RCF * %ΔRCF) part 1c
(%ΔRCF * %RCF) for V Plant



(Plant Type * %RCF * %ΔRCF) part 2a
(%RCF * %ΔRCF) for A Plant

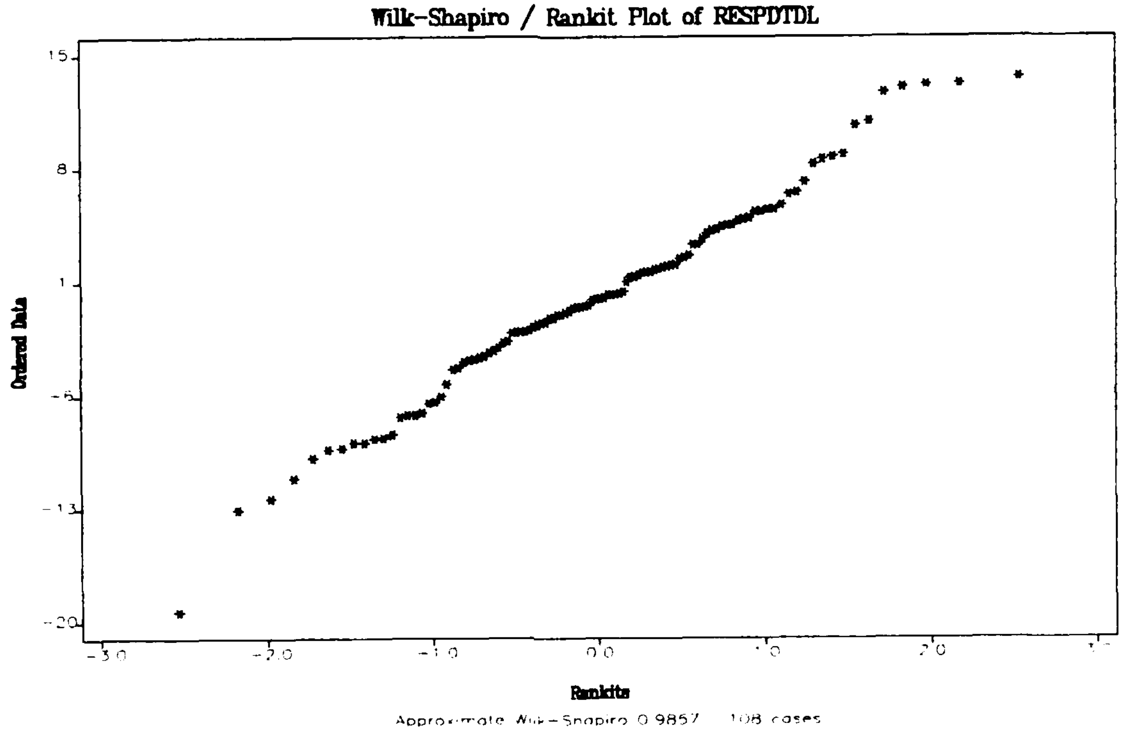


(Plant Type * %RCF * %ΔRCF) part 2b
(%RCF * %ΔRCF) for T Plant

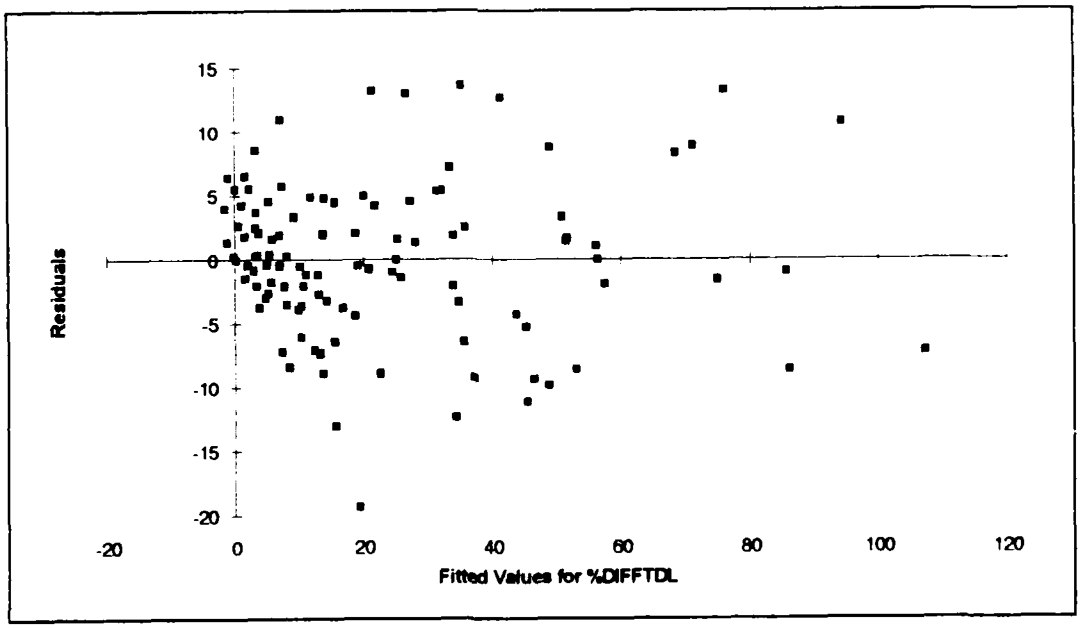


(Plant Type * %RCF * %ΔRCF) part 2c
(%RCF * %ΔRCF) for V Plant

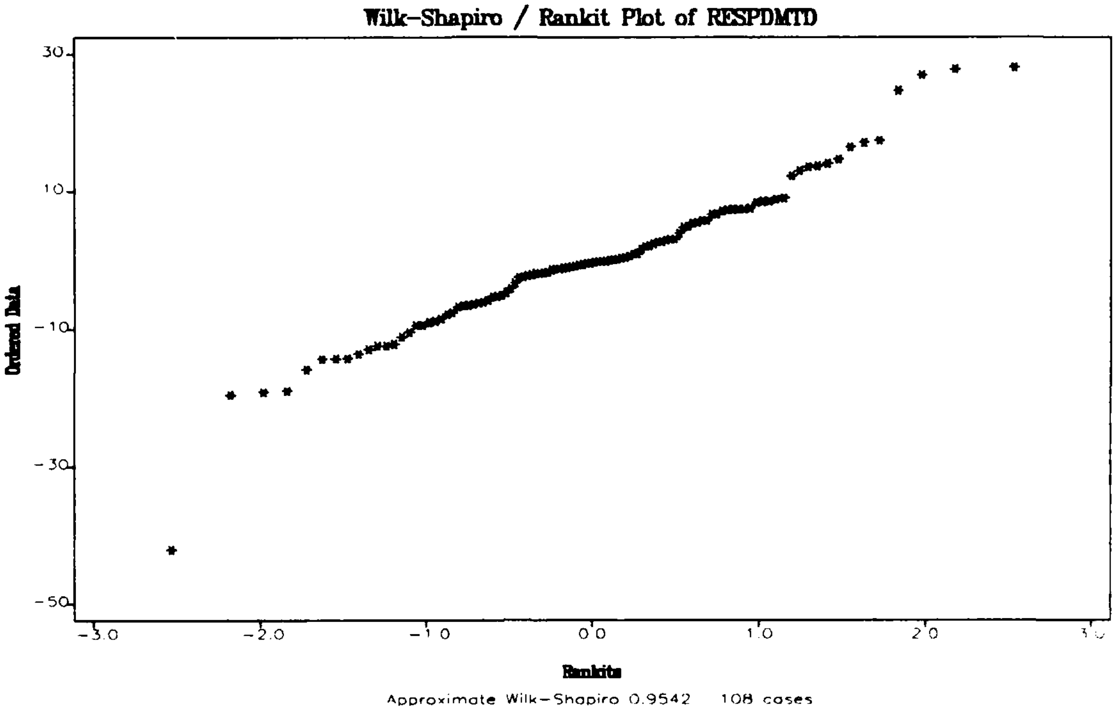
Appendix H: Assumptions of ANOVA Model for %DIFFTDL and %DIFFMTD



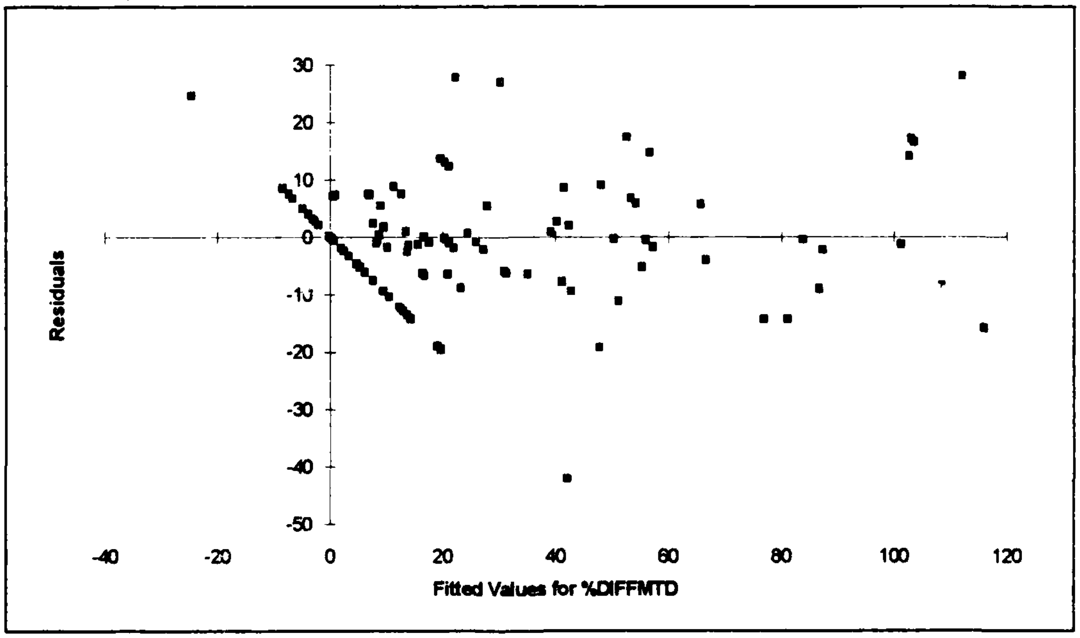
Normality Assessment Plot for %DIFFTDL



Constant Variance Assessment Scatterplot for %DIFFTDL



Normality Assessment Plot for %DIFFMTD



Constant Variance Assessment Scatterplot for %DIFFMTD

Appendix I: ANOVA Results for %DIFFTDL

STATISTIX 4.0 PDIFF, 08/09/93,
20:51

ANALYSIS OF VARIANCE TABLE FOR PDTDL

SOURCE	DF	SS	MS	F	P
PLANT (A)	2	11170.9	5585.48	2.16	0.1708
REP (B)					
A*B	9	23222.0	2580.23		
PRCF (C)	2	256.855	128.427	0.40	0.6785
A*C	4	3244.08	811.021	2.50	0.0788
A*B*C	18	5832.74	324.041		
PDELRCF (D)	2	4682.98	2341.49	7.53	0.0042
A*D	4	2559.96	639.991	2.06	0.1288
A*B*D	18	5594.90	310.827		
C*D	4	926.523	231.630	2.10	0.1010
A*C*D	8	1684.84	210.605	1.91	0.0888
A*B*C*D	36	3970.76	110.298		
TOTAL	107	63146.7			
GRAND AVERAGE	1	57738.5			

STATISTIX 4.0 PDIFF, 08/09/93,
20:51

TUKEY (HSD) PAIRWISE COMPARISONS OF MEANS OF PDTDL BY PDELRCF

PDELRCF	MEAN	HOMOGENEOUS GROUPS
25	30.150	I
50	24.898	I I
0	14.316	.. I

THERE ARE 2 GROUPS IN WHICH THE MEANS ARE
NOT SIGNIFICANTLY DIFFERENT FROM ONE ANOTHER.

CRITICAL Q VALUE	3.611	REJECTION LEVEL	0.050
CRITICAL VALUE FOR COMPARISON	10.609		
STANDARD ERROR FOR COMPARISON	4.1555		

ERROR TERM USED: PLANT*REP*PDELRCF, 18 DF

Number of observations in data set = 108
Grand Mean PDTDL = 23.123

Level of PLANT	Level of PCRCF	N	PDTDL Mean	PDTDL SD
A	H	12	27.6416667	16.6665947
A	L	12	21.1416667	14.0883871
A	M	12	30.2250000	24.3825990
T	H	12	23.7416667	25.4417859
T	L	12	45.3416667	40.1865753
T	M	12	31.8916667	27.0720405
V	H	12	11.5416667	13.7009428
V	L	12	7.0833333	8.9672975
V	M	12	9.5000000	8.5152270

Level of PLANT	Level of PCDRCF	N	PDTDL Mean	PDTDL SD
A	H	12	34.6166667	11.0529168
A	N	12	8.0666667	7.0861367
A	L	12	36.3250000	19.9603755
T	H	12	31.2916667	28.7164020
T	N	12	30.0666667	25.0086288
T	L	12	39.6166667	41.7822893
V	H	12	8.7875000	13.9501079
V	N	12	4.8250000	3.5024991
V	L	12	14.5125000	9.6372885

Level of PCRCF	Level of PCDRCF	N	PDTDL Mean	PDTDL SD
H	H	12	26.3458333	22.7491404
H	N	12	12.4250000	14.0400806
H	L	12	24.1541667	20.7315905
L	H	12	26.5333333	27.6027447
L	N	12	16.9750000	24.5300233
L	L	12	30.0583333	35.3174039
M	H	12	21.8166667	16.6488784
M	N	12	13.5583333	16.9804411
M	L	12	36.2416667	29.7716295

Level of PLANT	Level of PCRCF	Level of PCDRCF	N	PDTDL Mean	PDTDL SD
A	H	H	4	41.4250000	10.4767600
A	H	N	4	8.3000000	10.1518471
A	H	L	4	33.2000000	3.5194697
A	L	H	4	34.1750000	13.6700098
A	L	N	4	8.3000000	2.4385788
A	L	L	4	20.9500000	9.4093925
A	M	H	4	28.2500000	5.9332397
A	M	N	4	7.6000000	8.6413733
A	M	L	4	54.8250000	23.9874099
T	H	H	4	24.6750000	25.8667579
T	H	N	4	22.8750000	19.5063024
T	H	L	4	23.6750000	36.3541263
T	L	H	4	41.4000000	39.3909465
T	L	N	4	38.7000000	35.1517662
T	L	L	4	55.9250000	53.9013528
T	M	H	4	27.8000000	24.3320091
T	M	N	4	28.6250000	22.4943511
T	M	L	4	39.2500000	38.4772227
V	H	H	4	12.9375000	23.9191477
V	H	N	4	6.1000000	4.1952354
V	H	L	4	15.5875000	5.8873275
V	L	H	4	4.0250000	2.6663021
V	L	N	4	3.9250000	2.8300471
V	L	L	4	13.3000000	14.2276726
V	M	H	4	9.4000000	8.9784928
V	M	N	4	4.4500000	3.9920755
V	M	L	4	14.6500000	9.9968328

Appendix J: ANOVA Results for %DIFFMTD

STATISTIX 4.0 PDIFF, 08/09/93,
20:59

ANALYSIS OF VARIANCE TABLE FOR PDMTD

SOURCE	DF	SS	MS	F	P
PLANT (A)	2	24550.4	12275.2	4.05	0.0558
REP (B)					
A*B	9	27304.2	3033.80		
PRCF (C)	2	1799.30	899.651	3.33	0.0590
A*C	4	1084.69	271.173	1.00	0.4319
A*B*C	18	4868.76	270.486		
PDELRCF (D)	2	2484.84	1242.42	0.59	0.5655
A*D	4	845.939	211.484	0.10	0.9810
A*B*D	18	37997.2	2110.95		
C*D	4	1269.82	317.455	0.98	0.4316
A*C*D	8	932.836	116.604	0.36	0.9350
A*B*C*D	36	11683.7	324.549		
TOTAL	107	1.148E+05			
GRAND AVERAGE	1	81730.0			

Number of observations in data set = 108
Grand Mean PDMTD = 27.519

Level of PLANT	Level of PCRCF	N	PDMTD Mean	PDMTD SD
A	H	12	18.0416667	13.3157773
A	L	12	20.0666667	20.7732929
A	M	12	14.1083333	17.4590668
T	H	12	38.5833333	32.1380498
T	L	12	57.2333333	41.0567087
T	M	12	50.6500000	41.4041610
V	H	12	12.6833333	23.1573995
V	L	12	21.5250000	36.3211465
V	M	12	14.7750000	27.4294508

Level of PLANT	Level of PCDRCF	N	PDMTD Mean	PDMTD SD
A	H	12	13.9083333	11.8926607
A	N	12	17.3583333	19.9274803
A	L	12	20.9500000	19.1858139
T	H	12	49.2916667	29.4040028
T	N	12	41.8000000	43.0389887
T	L	12	55.3750000	42.5461274
V	H	12	17.0000000	25.8433744
V	N	12	7.0250000	11.2817733
V	L	12	24.9583333	41.0260108

Level of PCRCF	Level of PCDRCF	N	PDMTD Mean	PDMTD SD
H	H	12	25.4000000	23.8704458
H	N	12	20.6333333	30.0825632
H	L	12	23.2750000	25.8271219
L	H	12	33.0666667	32.7492494
L	N	12	25.9666667	30.3787705
L	L	12	39.7916667	47.9948001
M	H	12	21.7333333	28.2232764
M	N	12	19.5833333	34.9163893
M	L	12	38.2166667	38.5069258

Level of PLANT	Level of PCRCF	Level of PCDRCF	N	PDMTD Mean	PDMTD SD
A	H	H	4	17.5000000	5.0000000
A	H	N	4	18.7500000	23.9356777
A	H	L	4	17.8750000	7.1500000
A	L	H	4	21.4500000	14.3000000
A	L	N	4	18.7500000	23.9356777
A	L	L	4	20.0000000	28.2842712
A	M	H	4	2.7750000	5.5500000
A	M	N	4	14.5750000	17.1674838
A	M	L	4	24.9750000	21.5209007
T	H	H	4	41.7750000	26.2666297
T	H	N	4	39.5750000	42.6972579
T	H	L	4	34.4000000	35.1555591
T	L	H	4	59.6250000	37.5846046
T	L	N	4	45.8250000	41.6700032
T	L	L	4	66.2500000	52.3657967
T	M	H	4	46.4750000	28.9717535
T	M	N	4	40.0000000	56.5685425
T	M	L	4	65.4750000	42.1771166
V	H	H	4	16.9250000	28.9451637
V	H	N	4	3.5750000	7.1500000
V	H	L	4	17.5500000	30.1857030
V	L	H	4	18.1250000	29.9565658
V	L	N	4	13.3250000	16.3163262
V	L	L	4	33.1250000	58.2156551
V	M	H	4	15.9500000	26.6553935
V	M	N	4	4.1750000	8.3500000
V	M	L	4	24.2000000	41.3325538

Bibliography

Baker, Kenneth R. "Sequencing Rules and Due-Date Assignments in a Job Shop," *Management Science, 30*: 1093-1103 (September 1984).

Baker, Kenneth R. and J. W. M. Bertrand. "An Investigation of Due-Date Assignment Rules With Constrained Tightness," *Journal of Operations Management, 1*: 109-120 (February 1981).

Demmy, Steven and Arthur Petrini. "The Theory of Constraints: A New Weapon for Depot Maintenance Planning and Control," *Air Force Journal of Logistics, 16*: 6-11 (Summer 1992).

Devore, Jay L. *Probability and Statistics for Engineering and the Sciences* (Third Edition). Pacific Grove CA: Brooks/Cole Publishing Co., 1991.

DISASTER™ Version 1 Documentation, Avraham Y. Goldratt Institute (1990).

DISASTER™ Pamphlet, Avraham Y. Goldratt Institute (April 1991).

Dumond, John and Vincent A. Mabert. "Evaluating Project Scheduling and Due Date Assignment Procedures: An Experimental Analysis," *Management Science, 34*: 101-118 (January 1988).

Emory, C. William and Donald R. Cooper. *Business Research Methods* (Fourth Edition). Homewood IL: Irwin, 1991.

Fawcett, Stanley E. and John N. Pearson. "Understanding and Applying Constraint Management in Today's Manufacturing Environments," *Production and Inventory Management Journal, 32*: 46-55 (Third Quarter 1991).

Fox, Robert E. "Main Bottleneck on the Factory Floor?," *Management Review, 73*: 55-61 (November 1984).

Gargeya, Vidyaranya B. "An Evaluation of Resource Constraint Measures in a Dual Constrained Job Environment," *Proceedings of the 1992 Annual Meeting of the Decision Sciences Institute*. 1538-1540.

Goldratt, Eliyahu M. "Computerized Shop Floor Scheduling," *International Journal of Production Research, 26*: 443-445 (1988).

Goldratt, Eliyahu M. and Jeff Cox. *The Goal: A Process of Ongoing Improvement* (Second Revised Edition). Croton-on-Hudson NY: North River Press, 1992.

Goldratt, Eliyahu M. and Robert E. Fox. *The Race*. Croton-on-Hudson NY: North River Press, 1986.

Goldratt, Eliyahu M. *Sifting Information Out of the Data Ocean: The Haystack Syndrome*. Croton-on-Hudson NY: North River Press, 1990.

Graves, Stephan. "A Review of Production Scheduling," *Operations Research, 29*: 646-675 (July/August 1981).

Hahn, Gerald J. and Samuel S. Shapiro. Statistical Models in Engineering. New York NY: John Wiley and Sons Inc., 1967.

Heizer, Jay, et al. *Production and Operations Methods*. Needham Hts MA: Allyn and Bacon/Ginn Press. 1993.

Hicks, Charles R. *Fundamental Concepts in the Design of Experiments* (Second Edition). New York NY: Holt, Rinehart, and Winston, 1973.

Horngren, Charles T. and George Foster. *Cost Accounting: A Managerial Emphasis* (Seventh Edition). Englewood Cliffs NJ: Prentice-Hall, 1991.

Jayson, Susan. "Goldratt and Fox: Revolutionizing the Factory Floor," *Management Accounting, 68*: 18-22 (May 1987).

Kirk, Roger E. *Experimental Design: Procedures for the Behavioral Sciences* (Second Edition). Belmont CA: Brooks/Cole Publishing Company, 1982.

McKay, Kenneth N., et al. "Job-Shop Scheduling Theory: What Is Relevant?," *Interfaces, 18*: 84-90 (July/August 1988).

Miller, Phillip E., Lieutenant Colonel, United States Air Force. Professor in Logistics Management, Air Force Institute of Technology, Wright-Patterson AFB OH. Personal interview. 22 July 1993.

Moen, Ronald D., et al. *Improving Quality Through Planned Experimentation*. New York NY: McGraw-Hill, 1991.

Neter, John, et al. *Applied Linear Statistical Models* (Third Edition). Homewood IL: Irwin Inc., 1990.

Neufeldt, Victoria: Editor. *Webster's New World Dictionary* (Third College Edition). New York NY: Warner Books Inc., 1990.

Newbold, Robert C. Avraham Y. Goldratt Institute, New Haven CT. Attachment on Drum Logic. 27 August 1990.

Newbold, Robert C. Avraham Y. Goldratt Institute, New Haven CT. Personal Correspondence. 23 September 1992.

Ragatz, Gary L. and Vincent A. Mabert. "A Simulation Analysis of Due Date Assignment Rules," *Journal of Operations Management, 5*: 27-39 (November 1984).

Ramsay, Martin L., et al. "Push, Pull, and Squeeze Shop Floor Control with Computer Simulation," *Industrial Engineering, 22*: 39-45 (February 1990).

Reynolds, Dan. Class Lecture, STAT 536, Probability and Statistics II. School of Logistics and Acquisition Management, Air Force Institute of Technology, Wright-Patterson AFB OH, November 1992.

Reynolds, Dan. Professor of Probability and Statistics, Air Force Institute of Technology, Wright-Patterson AFB OH. Personal interview. 9 August 1993.

Rose, Coral. Avraham Y. Goldratt Institute, New Haven CT. Personal conversation with Jacob Simons. 22 Feb 93.

Schragenheim, Eli and Boaz Ronen. "Drum-Buffer-Rope Shop Floor Control," *Production and Inventory Management Journal, 31*: 18-23 (Third Quarter 1990)

Simons, Jacob and Richard Moore. "The Theory of Constraints Approach to Focused Improvement," *Air Force Journal of Logistics, 16*: 1-5 (Summer 1992).

STATISTIX™ 4.0 Manual. St. Paul MN: Analytical Software Publishing, 1992.

Turner, Jerry. "Finite Scheduling: MRP II's Final Frontier," *Manufacturing Systems, 9*: 62-64 (February 1991).

Umble, Dr. M. Michael and Dr. M. L. Srikanth. *Synchronous Manufacturing: Principles for World Class Excellence*. Cincinnati OH: South-Western Publishing Co., 1990.

Woolsey, Gene. "The Fifth Column: Production Scheduling As It Really Is," *Interfaces, 12*: 115-118 (December 1982).

Vita

Captain Stewart W. James was born 20 January 1963, in Fort Campbell, Kentucky. He graduated from the Louisiana State University in 1985 with a Bachelor of Science in Petroleum Engineering. He was commissioned through Officer Training School, entering active duty in July 1986. His first assignment was at 20th Tactical Fighter Wing, RAF Upper Heyford, England where he was both an Electronic Warfare Officer in the EF-111A and a Weapons Systems Officer in the F-111A. He entered the School of Logistics and Acquisition Management, Air Force Institute of Technology, in May 1992.

Permanent Address: 412 Davis Dr.
Luling, Louisiana 70070

Vita

Captain Bruno A. Mediate Jr. was born 15 September 1967, in Cleveland, Ohio. He graduated from the University of Notre Dame in 1989 with a Bachelor of Science in Aerospace Engineering. He was commissioned through the Reserve Officers' Training Corps, entering active duty in August 1989. His first assignment was at the Aeronautical Equipment Systems Program Office, Aeronautical Systems Division, Wright-Patterson AFB, Ohio, where he worked as project manager for the Standard Ring Laser Gyro Inertial Navigation Unit program. He entered the School of Logistics and Acquisition Management, Air Force Institute of Technology, in May 1992.

Permanent Address: 6999 Ivandale Dr.
Independence, Ohio 44131

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 1993	Master's Thesis

4. TITLE AND SUBTITLE

BENCHMARK PRODUCTION SCHEDULING PROBLEMS FOR JOB SHOPS WITH INTERACTIVE CONSTRAINTS

5. FUNDING NUMBERS

6. AUTHOR(S)

Stewart W. James, Captain, USAF
Bruno A. Mediate Jr., Captain, USAF

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Air Force Institute of Technology, WPAFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT/GSM/LAS/93S-9

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Air Force Materiel Command
Depot Maintenance Support Division
AFMC/LGD, WPAFB OH

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT *(Maximum 200 words)*

United States Air Force (USAF) depots have expressed interest in utilizing DISASTER production scheduling software to schedule their maintenance operations. DISASTER attempts to increase system throughput by building effective schedules for system constraint resources. However, when a system contains multiple, interactive constraints, DISASTER builds the constraint schedules one at a time. Since each successive schedule must adhere to timing restrictions imposed by previous constraint schedules, the quality of the schedules produced by DISASTER is dependent upon the sequence in which the constraints are scheduled. This thesis first developed a set of benchmark problems which provide a diversity of scheduling scenarios. These benchmark problems were then used to determine the relationship between the constraint scheduling sequence and the quality of the schedules DISASTER produced. The researchers found that the sequence in which the constraints were scheduled has an effect on the due date performance of the schedules. This knowledge has the potential to produce substantial improvements in the quality of USAF depots' schedules. In addition, the problems developed serve as a benchmark for future research which compares alternative scheduling algorithms to DISASTER.

14. SUBJECT TERMS	15. NUMBER OF PAGES
Scheduling, Theory of Constraints, Drum-Buffer-Rope	195
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

AFIT Control Number AFIT/GSM/LAS/93S-9

AFIT RESEARCH ASSESSMENT

The purpose of this questionnaire is to determine the potential for current and future applications of AFIT thesis research. Please return completed questionnaires to: DEPARTMENT OF THE AIR FORCE, AIR FORCE INSTITUTE OF TECHNOLOGY/LAC, 2950 P STREET, WRIGHT PATTERSON AFB OH 45433-7765

1. Did this research contribute to a current research project?

a. Yes b. No

2. Do you believe this research topic is significant enough that it would have been researched (or contracted) by your organization or another agency if AFIT had not researched it?

a. Yes b. No

3. The benefits of AFIT research can often be expressed by the equivalent value that your agency received by virtue of AFIT performing the research. Please estimate what this research would have cost in terms of manpower and/or dollars if it had been accomplished under contract or if it had been done in-house.

Man Years _______________ $ _______________

4. Often it is not possible to attach equivalent dollar values to research, although the results of the research may, in fact, be important. Whether or not you were able to establish an equivalent value for this research (3, above) what is your estimate of its significance?

a. Highly Significant b. Significant c. Slightly Significant d. Of No Significance

5. Comments

_______________________________ _______________________________

Name and Grade Organization

_______________________________ _______________________________

Position or Title Address