UNIVERSITY OF CALGARY

Input Control Strategies for Make-to-order Manufacturing Systems via Order Acceptance/Rejection

by

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A DISSERTATION

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF MECHANICAL AND MANUFACTURING ENGINEERING

CALGARY, ALBERTA

SEPTEMBER, 2000

0-612-64831-1

Abstract

The ability of manufacturing organizations to reliably meet due dates that have been promised to their customers is of primary importance. In a make-to-order manufacturing environment where capacity is fixed and due dates cannot be influenced, rejection of a judiciously chosen subset of potential customer orders represents one way to manage the situation. This thesis exclusively focuses on this kind of manufacturing system and explores in detail how the ability to reject orders affects performance when costs arise due to both job rejection and job tardiness.

In this research three alternative rules (two algorithmic and one simulation-based) for making the accept/reject decision for customer orders have been developed and tested. A wide range of experiments have been conducted and analyzed to assess both the qualitative and quantitative performance of these rules. In addition, the thesis reports on how an optimal control policy for a hypothetical manufacturing system can be chosen as a function of the system's environmental factors.

Acknowledgements

My thesis is an apex built on so many experiences at the University of Calgary and which has been influenced by many people whom I wish to acknowledge here.

First of all I would like to thank Dr. Paul Rogers for supervising me, for giving me direction at the difficult times during my research, and also providing me with financial support.

Next, I would like to thank Dr. S.T. Enns for his invaluable informal advice and discussion on many critical research issues.

The help and support of Mr. Khee Teck Wong, our computer system manager, deserves special mention. During many computer problems he was always there and most importantly he solved all problems in a timely fashion. Also I wish to thank all of our departmental staff and all of my friends in the department.

I would also like to thank my examining committee Dr. P. Rogers, Dr. D.H. Norrie, Dr. S.T. Enns, Dr. J. Balakrishnan and Dr. D.R. Strong.

My parents and elder brother deserve very special thanks for sharing my agony and providing me emotional support at difficult situations. Also many appreciation is reserved for Shilpi, for her patience and understanding attitude.

Finally a special thanks should go to the Natural Science and Engineering Research Council of Canada and to the Department of Mechanical and Manufacturing Engineering for their uninterrupted financial support which has made this research possible.

Dedicated to my Parents

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Chapter 1

Introduction

Those involved with the management of manufacturing operations are faced with the difficult task of balancing often conflicting objectives such as productivity and speed of customer response. Furthermore, the relative importance of different objectives changes over time. It is widely recognized today that the objective of high capacity utilization has gradually lost importance compared with the need for low inventories, short lead times and high due date performance and that competing in a global market demands high quality, dependable deliveries. Being a low cost producer no longer guarantees success (Hill, 1985), while the ability to distinguish one manufacturer from another based on high product quality has been replaced by time and service-related capabilities (Miller and Roth, 1988). In highly competitive markets, many companies have come to view customer satisfaction as a key to maintaining and increasing their market share. One of the most important measures of the quality of service a company provides is on-time delivery performance (Ashby and Uzsoy, 1995), although it should be recognized that this is not a new concern as Conway *et al.* (1967) noted:

> "The measure that arouses the most interest in those who face practical problems of sequencing is the satisfaction of preassigned due dates ... the ability to fulfill delivery promises on time undoubtedly dominates these other considerations."

The ability to reliably meet due dates, particularly in situations where allowable flow times are short, is coupled with the ability to keep work in progress (WIP) levels under control. It is now a generally accepted fact that as WIP increases beyond a certain point, the throughput ceases to increase, while manufacturing lead time (MLT) continues to rise. In a seminal work, Little (1961) showed the theoretical relationship among WIP, throughput and MLT, highlighting that there is a critical level of WIP that should not be exceeded in a manufacturing system if lead time guarantees are to be achievable.

Managing and controlling WIP inventories requires well-defined Order Review and Release (ORR) strategies. Wight (1970) advocated long ago for serious consideration of input/output control within the production planning and control system suggesting a simple principle which states that *work should not be added to the shop at a rate that exceeds the rate at which the work can be completed*. This principle has become known as the principle of Workload Control (WLC).

Research in ORR can be traced back to the 1960s with a substantial volume of research appearing since then. One concept which has not been well investigated in the existing ORR literature is how the ability to selectively reject customer orders might affect the performance of a manufacturing organization. From the point of view of overall customer service, rejecting some selected orders, so that the accepted orders can be finished with an acceptable level of tardiness, may be better than accepting all orders and finishing a significant proportion of them tardy, and with the overall tardiness unacceptably high. In fact, rejecting some orders is the only way to manage a make-to-order manufacturing system where capacity is fixed and where due dates cannot be influenced, once they are assigned.

The present thesis is intended to explore the concept of selective order rejection and thereby contribute to the body of knowledge on input control. The thesis exclusively focuses on a fixed capacity make-to-order manufacturing system and explores in detail how the ability to reject orders affects performance when costs arise due to both job rejection and job tardiness.

The rest of the thesis is arranged in the following way. Chapter 2 presents a detailed literature review in the area of workload control which leads to a logical set of objectives for this thesis. Chapter 3 includes a description of the hypothetical manufacturing system which has been used as a test bed for the research. Chapter 4 reports on some preliminary studies of the system, exploring how different factors impact the principal performance measures both when the system is operating without the ability to reject any orders and when an explicit accept/reject capability is added. Chapter 5 explores how optimal control parameters can be chosen as a function of the system's environmental factors. This chapter reports on the effect of this optimal control on the main performance measures of the system. Finally Chapter 6 concludes this thesis highlighting the main contributions of the research and identifying some promising directions for further work.

Chapter 2

Review of Relevant Literature

This chapter outlines the motivation and objective of the present research through an extensive literature review in the area of Workload Control (WLC), which encompasses both input and output control. This review analyzes the merits and demerits of a sizeable body of research that has been reported to date and identifies the gaps which are worthy of further research for this thesis. The chapter begins with a general discussion of input/output control, and subsequently focuses on the Order Review and Release (ORR) mechanism, which is the key instrument for input control. While doing so, the pros and cons of ORR, as noted in the existing literature, are addressed and the position of ORR in the context of a typical Production Planning and Control System is identified, which is useful in presenting a framework for ORR. The chapter concludes with a statement of the specific objectives of the thesis.

2.1 Input/Output Control

High volumes of work in process, plants running behind schedule and due dates being frequently missed are some of the common happenings on the shop floor which cost manufacturers money. As Wight (1970) pointed out, these are the symptoms of a problem sometimes called long Manufacturing Lead Time (MLT). Wight showed that the actual working time of a job in the manufacturing shop is in fact ten percent or less of the MLT, which is the total time spent by the job in the shop. This is because it spends most of the time waiting in various machine queues, the queues being out of control.

It is now well known that as work in progress (WIP) increases beyond a limiting point, the throughput ceases to increase, while MLT continues to rise. In a pioneering work, Little (1961) showed the theoretical relationship among WIP, throughput and MLT. This gives an indication that there is a critical level of WIP that should be maintained in the system to avoid problems with long lead times while achieving satisfactory throughput.

The three main causes of uncontrolled queues, identified by Wight (1970), are inflated planned lead time, erratic input to the plant, and inability to plan and control output effectively. Each of these three is explained in more detail below.

It is a common misconception that *longer planned lead times* to the customer help meeting due dates since in reality the opposite may be true as longer lead times may cause more work to be released to the floor which causes greater congestion and longer delays. "As planned lead times are increased, orders will be generated sooner, thus increasing backlogs in the shop." (Wight, 1970)

The second cause is *erratic plant input*. Releasing jobs to the manufacturing floor as the system generates requirements, may result in a highly erratic input to the shop. Existing traditional production planning and control systems provide insufficient support to coordinate the different planning levels which are concerned with the scheduling of the work orders. With highly uneven input and fixed capacity of resources, it can be difficult to produce the output at the same rate as the input, so this extra input gets absorbed into the queues and the backlogs increase and hence the lead time. Putting orders into a shop on the date when they are supposed to be started, regardless of available capacity, doesn't really make a great deal of sense. On the shop floor, if there is not enough capacity, and the rate of input exceeds the rate of output, the orders are likely to show up tardy and it is hard to determine what the real priorities are, as they are changed since the orders were originally released. A low level of shop backlog (*i.e.* the jobs which are behind their planned progress through the shop) can be maintained only if the jobs are released to the shop at a rate which matches the capacity of the shop. In particular, if the capacity remains constant, so should the release rate. This emphasizes the importance of controlling the input of work load into the system.

The third reason which might cause uncontrolled queues is the *lack of control of output*. There is one simple rule to control backlogs, and thus control lead times, which is to keep the rate of input to the shop equal to or less than the rate of output from the shop. It allows the production manager to control another factor which is the rate of output. This can be managed by adjusting the resource capacity in the shop, as and when needed through overtime, subcontracting or extra shifts.

So, controlling the input of work load to the manufacturing system involves judiciously accepting customer orders and/or releasing the accepted orders to the shop floor when the time is ripe. Controlling the output deals with manipulating the capacity of the resources available to the manufacturing system, which might permit the system to deal with some variability in workload. When the balance between capacity available and demand is unacceptable, the planning system can reestablish balance by increasing capacity in the periods where the load exceeds the capacity (*e.g.*, through overtime, subcontracting or extra shifts as mentioned earlier). This capacity problem can also be handled by shifting and readjusting the orders to different periods and making appropriate changes to the due dates. This input/output control stems from Wight's principle of Workload Control (WLC) and the concept has attracted much interest during the last decade.

The present research explores the situation where the capacity remains constant and thus is devoted only to input control of manufacturing systems which is typically known as the Order Review and Release (ORR) mechanism.

2.2 The Order Review and Release (ORR) Mechanism

This section gives an overview of the ORR mechanism, illustrates the position of ORR in the context of Production Planning and Control of manufacturing systems, and describes a framework for ORR.

2.2.1 The Place of ORR in the Production Planning and Control System

In the existing literature dealing with ORR, there is some confusion regarding the place of ORR in the context of Production Planning and Control Systems. For example, Melnyk and Carter (1987) considered ORR as a shop floor control activity. At the same time, the order release pool (which is generally referred to as a *pre-shop* pool) is an important component of ORR and has been said to connect the planning system and the shop floor, indicating that ORR is not wholly a part of either the planning system or the shop floor. On the other hand, Philipoom and Fry (1992) and Bergamaschi *et al.* (1997) recognized the decision of order acceptance or rejection as one of the ORR activities. But the activity of accepting an order is generally known as an activity for which the planning system is responsible. So ORR is partly a planning activity as well.

In this thesis ORR will be viewed as neither a part of the planning system nor of the shop floor, but it certainly helps the planning system to make the order accept/reject decision. It also includes the preparation of accepted orders in terms of accumulating all the information about the order required by the shop floor personnel. As long as the order preparation phase is not complete, the order does not leave the planning system. After the planning system, an order may be temporarily held back in the order release pool which is a pre-shop pool for review and evaluation of the order and possibly for leveling the load on the shop floor by choosing the appropriate time to release the order.

2.2.2 What is ORR?

ORR deals with controlling the input of orders to a manufacturing system. Broadly speaking, it is the process of managing order transition from the customer or the planning system to the shop floor. These activities are necessary to control the flow of information and orders passing from the planning system to the execution system and to ensure that the orders which are accepted and released have a reasonable chance of being completed in the desired time and quantity. It is worth noting explicitly that ORR might choose to reject some of the orders.

2.2.3 A Framework for the ORR Mechanism

ORR consists of all of the activities that take place from the time when the planning system faces a request from a customer to accept an order until that order (if accepted) is in process on the floor. At least two frameworks for ORR can be found in the existing literature. The first, and the most recognized and detailed one, was developed by Melnyk and Carter (1987) while a second one was developed by Bechte (1988).

According to Bechte (1988), a complete ORR system, in its most general form, consists of three major parts which are *order entry phase*, *pre-shop pool management phase*, and *order release phase*. In contrast, according to Melnyk and Carter (1987), ORR in its most basic form consists of three major activities *viz. order preparation*, *review and evaluation of orders*, and *load leveling*. In both of these frameworks, the activity of order accept/reject decision-making was not considered specifically, since the concept of this kind of decision-making as a means to control the input of orders in a manufacturing system was not explicitly recognized until Philipoom and Fry (1992). Later on, Bergamaschi *et al.* (1997) incorporated the activity of accept/reject decision-making into the *order entry phase* of the framework developed by Bechte (1988).

In the following paragraphs the ORR framework will be described briefly according to the guideline laid by Melnyk and Carter (1987) with the necessary modification to incorporate the accept/reject decision as suggested by Bergamaschi *et al.* (1997) and Philipoom and Fry (1992).

2.2.3.1 The Activities of ORR

ORR is essentially an interface between the customer/manufacturing planning system and the shop floor. In its modified form, ORR consists of *four* major activities *viz. (1) Accept/reject decision-making for an order, (2) order preparation, (3) review and evaluation of orders,* and *(4) load leveling.*

(1) Accept/reject decision-making for an order: This activity decides if a particular order will be accepted or rejected depending on some criterion (*e.g.* shop floor condition, nature of the order *etc.*).

(2) Order preparation: This ensures that the order released by the planning system has all of the information required by the shop floor personnel.

(3) Review and evaluation of orders: This activity attempts to ensure that orders are completed in a timely and cost effective manner by preventing the release of problem orders. Problem orders are those which are infeasible due to problems in capacity, tooling or material availability.

(4) Load leveling: This tries to level the capacity utilization over time by smoothing out the peaks and valleys in load on the shop floor. This smoothing is achieved by controlling the time at which orders are actually released to the shop floor. Orders may be held back in an "order release pool".

2.2.3.2 The Components of the Framework

ORR functions are achieved via coordination between four major components:

(1) The order release pool,
(2) The shop floor,
(3) The planning system,
(4) The information system, linking the planning system, the shop floor and the order release pool.

2.2.3.2.1 The order release pool

The order release pool contains all the jobs which have been released by the planning system to the shop floor control system but have not yet been released to the shop floor. Thus the order release pool is a storage area for these unreleased orders, and is also an indicator of free capacity available since an increase in the size of the order release pool indicates some capacity shortage in the shop. The pool is managed by specifying the *timing convention, triggering mechanism* and *order selection rule* governing the release of orders from the pool to the shop floor.

The *timing convention* determines when a release can occur. In the case of continuous release, a job can be released at any time when the system is operative. On the other hand, for a bucketed timing convention, a release can take place only at some periodic time instants.

The *triggering mechanism* determines, without violation of the timing convention, when a release actually should take place. There are three kinds of triggers possible: *(a) pool-based, (b) shop-based,* and *(c) pool and shop based.* With a *pool-based trigger*, the time of release of a job from the order release pool is dependent only on the information about the jobs in the pool, while in the case of a *shop-based trigger*, the release of work is based on current conditions on the shop floor. According to the third kind of triggering mechanism, a job can be released on the basis of information on both the pool and the shop floor.

Whenever the timing convention and triggering mechanism allow an order release to take place, it is necessary to select which job is to be released via the *order selection rule* which can be either *local* or *global*. A selection rule is very similar to a dispatching rule. A local selection rule selects a job by strictly using information about the jobs in the pool, while a global selection rule uses information not only from the pool but also from the shop conditions.

2.2.3.2.2 The shop floor

Order Review and Release in essence attempts to balance the load released to the shop floor against the available capacity on the shop floor. This requires information describing current load and capacity conditions on the shop floor. This information can be presented in the form of *total shop load* or in the form of *load by work centre*. In the former case, the load is reported as one measure and no information is supplied on how the load is distributed over different work centers. When the load information is presented as a distribution over the work centers, the total work load is broken down and reported by work center.

In the presentation of load information, two basic approaches can be followed regarding time. One is the *instantaneous load* approach and the other is the *load profile* approach. In the former case, a snapshot of the shop load at a particular time is used and in the later case, load is reported as the amount of load per period of time over a given time horizon, *e.g.* a shift or a week.

2.2.3.2.3 The planning system

An important aspect of the ORR process is the flow of orders from the planning system to the order release pool. The planning system generates the schedule of planned order releases which implicitly identifies the future demands on shop capacity. There are two issues which are important in the use of this schedule. One is *schedule visibility* and the other is *schedule feasibility*. *Schedule visibility* is the amount of information given to ORR about future planned order releases. When ORR is informed of only those orders which are mature in the current period of time, it is said that the schedule visibility is *limited*. On the other hand, in the case of *extended* visibility, ORR is informed about both the releases in the current period and in periods some distance into the future. This latter type of visibility helps identification and analysis of both the current and future demands on shop-floor resources.

Melnyk and Carter (1987) consider two types of *schedule feasibility* referred to as *controlled* and *uncontrolled*. An *uncontrolled* schedule is one which is prepared without evaluating the period-to-period feasibility, and a *controlled* schedule is one which is prepared after evaluating the period-to-period capacity feasibility (*i.e.* checking that demand is less than capacity).

2.2.3.2.4 The information system

As per Melnyk and Carter (1987), the information system, the fourth component of the ORR system, links the planning system, ORR and the shop floor. Factors reflecting the quality of information that may have effects on the performance of ORR are *timeliness*, *accuracy* and *completeness*. *Timeliness* is the speed with which changes are reflected in the information supplied to ORR. In practice, there is always a delay between a change and when it appears in the database. The *accuracy* and *completeness* are also affected by the information system. The information system may introduce errors to the data or omit important data. As accuracy deteriorates, the effectiveness of ORR also must worsen.

When these four components *viz.* the order release pool, the shop floor, the planning system and the information system are combined, the entire span of decisions involving ORR is defined.

2.3 Pros and Cons of Input Control

Although input control of work load has the potential to solve some of the crucial problems in the management of manufacturing, the approach is not free from criticism. These criticisms are addressed in detail under category (h) of section 2.4 which reviews the existing literature in detail.

There are a number of immediate benefits of ORR which are readily available and upon which most researchers agree. Some of those which were listed by Lingayat *et al.* (1991) are as follows:

(1) It controls the level of WIP, by moving the queues from the shop floor to the order release pool. Shifting the queue to the pool may give the system added flexibility by delaying the latest date for cancellation of, or changes to an order and also, it reduces the physical congestion on the shop floor.

(2) It serves as a screening process, since it does not release an order until all the information and resources for processing the order are available.

(3) It provides a simple mechanism to handle the important (so called "hot") orders since it decides which order to release to the shop floor.

(4) It works as an indicator of capacity availability. A large increase in the size of the order pool may point to problems with capacity on the shop floor.

In addition, Ragatz and Mabert (1988) commented that compelling reasons exist for *not* releasing jobs as they are received, even when material is available and all pre-production activities have been completed. Parts delivered to the finished stockroom or to the assembly floor long before they are needed tie up unnecessary capital. Moreover, parts on hand too soon may disappear, may be damaged by excessive handling or may occupy valuable space too long. In addition, jobs released to the shop floor too early will compete for resources (machine time) with more urgent jobs and may interfere with the progress of those jobs.

2.4 A Detailed Review of Relevant Literature

The literature on input control is plentiful. According to Wisner (1995), "LeGrande (1963) was perhaps the earliest author to utilize a delayed release mechanism in his experiments, who used finite forward loading as the order release rule." Ackerman (1963), during the same period, reported research where the author experimented with a dynamic job shop, where he used simple backward infinite loading (BIL) to determine release dates and to plan overtime. In other early research, Harty (1969) identified the bottleneck resources and controlled the release of work to the shop so as not to overload these resources. In all of these early research works, the importance of order release has been recognized and considered as a vital component of shop floor control. So, the importance of delayed and judicious release of orders is clearly not, in isolation, a new concept.

However, Wight (1970) is probably the most well-known author from the 1970s to realize the importance of input control and to advocate for serious consideration of input/output control within production planning and control systems. He suggested the simple principle of workload control which says that work should not be added to the shop at a rate that exceeds shop capacity, *i.e.* the rate at which work can be completed.

To date, it is possible to find a large body of research works focusing on different aspects of input/output control. In the following text, a number of such works are highlighted, grouped into eight categories according to their underlying theme. Some of the order release rules that are addressed by different authors as mentioned below, have been briefly described in **Appendix A**, although the list therein is not an exhaustive one.

The research literature will be described under the following categories:

(a) General discussion, overview, and perspective of ORR,

(b) Interaction between order release decisions and other activities on the shop floor *e.g.* priority dispatching, due date setting rules *etc.*,

(c) Interaction between ORR and the planning system,

(d) ORR by controlling the workload on the bottleneck machine,

(e) ORR by controlling the arrival process,

(f) ORR viewed as a step towards JIT,

(g) ORR by controlling the output,

(h) Criticism against ORR.

(a) General discussion, overview, and perspective of ORR

The research papers that are available in this category are mainly general discussions of ORR. Some of them surveyed existing research in ORR and at least a couple of them contributed towards building a framework of ORR. The most significant articles are Melnyk and Carter (1987), Melnyk (1988), Melnyk and Ragatz (1988, 1989), Melnyk *et al.* (1994b), Wisner (1995), Land and Gaalman (1996), and Bergamaschi *et al.* (1997).

Melnyk and Carter (1987) is the first research which contributed an overall framework of ORR. This has been previously discussed, in detail, above. It reveals different components of ORR, and is important in the sense that it indicates possible areas where practitioners can focus their attention to improve the effectiveness of ORR. This framework is fundamental in its nature and has been followed and reiterated in subsequent work, *e.g.* Melnyk (1988), Melnyk and Ragatz (1988, 1989), and partly by Bergamaschi *et al.* (1997).

Melnyk (1988) discussed ORR issues in the broad context of production control. The author evaluated the status of research in ORR and commented that there has been very little research to date on ORR systems in environments which are characterized by long time horizon, extended schedule visibility and smoothed planned load. He also envisaged that order release has to play a far more important role in the case of flexible manufacturing systems and group technology based work cells than in the case of job shop environments and that there has been little research done so far in this direction.

Wisner (1995) is the first survey paper on ORR research. The author categorized the order release policies into *finite loading techniques* (*i.e.* orders are released when the shop or machine loadings are less than the desired loadings) and *infinite loading techniques* (*i.e.* orders are released at a predetermined release date, regardless of current shop or machine loadings). He further subdivided each of them into *forward* and *backward* loading techniques. He also presented various characteristics of the simulation-based ORR research in a tabular form. The paper concluded with some directions for further research.

Bergamaschi *et al.* (1997) is a comparatively more recent and up-to-date review of existing ORR research. In this paper, the authors presented a general structure of ORR, a literature review, a framework and a critical analysis of ORR methods. They also suggested some future research paths. Eight main dimensions were considered in this framework that describe the fundamental principles, characteristics and logic of existing ORR techniques.

(b) <u>Interaction between order release decisions and other activities on the shop floor *e.g.* priority dispatching, due date setting rules *etc.*</u>

Researchers have studied the interaction of order release decisions with other functions of scheduling such as due date setting and priority dispatching. Among them, the noted ones are Ackerman (1963), Irastorza and Deane (1974), Adam and Surkis (1977), Bertrand (1983b), Shimoyashiro *et al.* (1984), Morton *et al.* (1988), Ragatz and Mabert (1988), Melnyk and Ragatz (1989), Park and Bobrowski (1989), Bobrowski and Park (1989), Mahmoodi *et al.* (1990). Ahmed and Fisher (1992), Melnyk *et al.* (1994a, 1994b), Ashby and Uzsoy (1995).

Ackerman (1963) compared several "even-flow" scheduling rules (which are combinations of BIL release and one of three due date oriented dispatch policies), with IMR and four dispatch policies in a job shop setting. He found that even-flow rules provided higher reliability in on-time completion than any other rules involving IMR. In this study, the necessary adjustment of the shop capacity was allowed.

Irastorza and Deane (1974) devised an algorithmic procedure for loading and releasing work to a job shop environment. This rule is fundamentally a FFL rule with the objective being to control and balance workloads among the machine centers. The importance of shop balance is justified and several measures of performance are derived. They found that their FFL rule outperformed IMR when paired with the dispatch rules Dynamic Slack per Operation (DSOP) and Shortest Processing Time (SPT), in terms of several workload-oriented performance measures such as Machine Work Balance Index (MWB), Shop Work Balance Index (SWB), Machine Queue Balance Index (QWB), Aggregate Desired Loading Deviation ($\overline{D}$), WIP (in hours) *etc.* For the definitions of these measures, please see **Appendix A**.

Adam and Surkis (1977) studied a dynamic capacity planning approach in a job shop environment with six work centers, which views the shop as a dynamic statistical system, taking into account the expected congestion that a job might encounter as it proceeds through the shop. They compared it with BFL and BIL. The study showed that the dynamic approach is better than BFL which is in turn better than BIL in terms of average lateness and the number of tardy jobs. They tested these in conjunction with two dispatch rules.

Bertrand (1983b) studied the performance of a work load dependent scheduling and due date assignment rule through computer simulation. The rule used time-phased work load information and time-phased capacity information. The two releasing methods considered in this research were random release and a controlled release to maintain a specific work load norm. The results showed that time-phased workload information may decrease the variance in lateness as compared with time-aggregated (*i.e.* non-time-phased) information only. It was shown that by selecting appropriate parameter values, both a constant mean lateness and a small variance of lateness can be obtained with this type of assignment rule.

Shimoyashiro *et al.* (1984) studied order release methods in a job shop, based on the work load balance across machines and across time periods simultaneously and also considering the limitation of the work input into the shop. They compared FFL and IMR using MSOP and FCFS dispatching and found that FFL outperformed IMR in all cases in terms of machine utilization, flow time, and job lateness.

Morton *et al.* (1988) used a cost-based performance measure to compare a dynamic FFL heuristic with eight other combinations of release and dispatch rules, in different shop floor configurations and found that the controlled release heuristic performed better than other policy combinations.

Ragatz and Mabert (1988) evaluated five releasing mechanisms and four dispatching rules under three levels of due-date tightness, shop cost structure, and machine utilization using simulation. In this paper, the five mechanisms that were tested were IMM, BIL, MIL, MNJ, BFL. The four dispatching rules that were considered were FCFS, SPT, EDD, and CR. The results of this study showed that controlling the release of work to the shop floor in a job shop system can substantially improve the performance of the system in terms of total shop cost, jobs on the shop floor, deviation from due dates, and job queue times. The total cost consists of late delivery cost and holding cost for both work in progress and finished-goods inventory. In this study, the strong performance of the MIL rule suggested that both information about the characteristics of the job and about current shop congestion can be useful in setting release dates. The total cost performance of BFL varied but the sensitivity analysis showed that under lower levels of utilization or lower lateness cost to holding cost ratios, BFL can provide very good results.

Melnyk and Ragatz (1989) examined the ORR function and its impact on the operation of the shop floor. They attempted to provide a better understanding of this element by presenting a framework for ORR. This paper also explored the relationship between ORR and job dispatching through a computer simulation model. The results showed that the presence of an order release mechanism can have a significant effect on the performance of the production system. The use of either the WCEDD or AGGWNQ release mechanisms, when compared to the NORR, resulted in poorer performance in terms of the delivery performance measures: however the use of either WCEDD or AGGWNQ resulted in better performance when evaluated using the WIP and workload balance measures. Another conclusion identified by the study was that while controlling order release may not reduce the total time an order spends in the system, it does influence where the order spends its waiting time.

Park and Bobrowski (1989) examined the role of labour flexibility in conjunction with the shop's ability to regulate the type and number of jobs active on the shop floor for processing. The release mechanisms that regulate the jobs on the shop floor considered both job and shop information in determining the job release time. Two release mechanisms with three labour flexibility and two labour assignment rules were simulated in this study using two levels of job due date tightness. Results showed that there was no statistically significant difference in the performance using finite loading and infinite loading release mechanisms.

In another paper, Bobrowski and Park (1989) studied the effects of several release mechanisms on the performance of a dual resource constrained job shop. Four release mechanisms were tested in conjunction with two dynamic, due date oriented dispatching rules. The job shop environment was specified by two levels of due date tightness. A labour and machine limited job shop model was used to simulate the shop performance. For the dual resource constrained job shop, the research indicated that release mechanisms developed initially for the machine constrained shop are applicable and produce significant performance improvements over an immediate release rule.

Mahmoodi *et al.* (1990) studied a controlled comparison of three order releasing and two due date assignment heuristics (in one due date is internally set, while in the other it is set externally) in conjunction with six scheduling heuristics in a cellular manufacturing environment. In the controlled release mechanism, the release time for an order is estimated by subtracting a flow time estimate of the order from its due date. The flow time of the order is calculated as the sum of the total processing time of the order and a weighted total number of jobs on the route of the order. Results showed that controlled release deteriorates flow time, lateness, and tardiness performance and was inferior to both immediate and interval release. Under the mechanism of interval release, all jobs were released to the shop every four hours. Controlled release seemed to work best in the case of low load and tight due dates. Analysis of different dispatching rules showed the relative performance remained unchanged by the presence of different order release mechanisms. Comparison of internally and externally set due date mechanisms indicated simpler, non-due date oriented heuristics demonstrated as good a performance as the more complex due date oriented heuristics when shop information was utilized to assign job due dates. The authors found that in a manufacturing cell, the use of shop floor information was effective for due date assignment, but was not worthwhile for order releasing. The poor performance of controlled order release, according to the authors, can be overcome by more accurate and precise estimation of flow time, and more effective releasing mechanisms.

Ahmed and Fisher (1992) studied the interaction between due date assignment, job order release rules and sequencing rules. The authors used a dynamic five-machine job shop in which early shipments are prohibited. Performance of the system was measured primarily in terms of the total cost (*i.e.* WIP cost, finished goods holding cost, and late penalty cost) incurred by the shop. The results support existence of a three way interaction between the due date, release, and sequencing procedures as well as an interaction between shop utilization and different combinations.

In a comparatively recent study, Melnyk *et al.* (1994a) experimented with a situation where the time interval between two successive releases is sampled from a distribution and studied the impact of different types of distribution as well as the variation of parameters within the same type, on shop performance. The authors performed a simulation study of a random job shop with a full factorial experimental design, and demonstrated that the type of distribution does affect the performance. Moreover, this research concluded that the performance of the shop floor is affected by the way the orders are released by the planning system.

Melnyk *et al.* (1994b) studied the combined effect of variance control (variance created in the planning system through uneven load and also in the shop floor through varying process times of the released batches), ORR and dispatching rules in a simulated job shop. The authors carried out a full factorial experiment with two types of job release by the planning system (*viz.* one is as-is and the other one is with smoothing peaks and valleys of weekly loads planned to be released), two ORR mechanisms (*viz.* immediate release and load limited release), two levels of process time distribution (exponential and uniform with identical mean process time for each distribution) and five dispatching rules (*viz.* FCFS, SPT, MINSLK, S/OPN, CRR). The authors found that the presence of variance control at both the planning and shop floor levels can greatly enhance the effectiveness of ORR and also if used effectively, variance control can greatly reduce the need for a complex dispatching rule.

Ashby and Uzsoy (1995) reported on the development of a number of scheduling policies integrating order release, group scheduling, and order sequencing for a group technology cell in the presence of sequence-dependent setup times and dynamic job arrivals. Results show that the new scheduling policies, which consider setup times as well as due dates in both order release and job sequencing decisions, substantially improve due date performance.

(c) Interaction between ORR and the planning system

There are interactions between the planning system and the ORR decisions. In this line of research, there are not many research works available. Wisner (1995) has mentioned two of them. They are by O'Grady and Azoza (1987) and Melnyk *et al.* (1991).

O'Grady and Azoza (1987) used an order release policy based on the weighted sum of the *net excess stock* over the planning period and a *workload smoothing value* for each job. The jobs were loaded to the shop in the current planning period in the ascending order of the above mentioned weighted sum until a value of upper input workload for the current period was reached. The weights were varied and combined with FCFS and SPT dispatching at various levels of shop loading, and an optimal weight for the release function was found using total cost as a performance measure. While computing the *net excess stock* for the current period, WIP, present stock levels, expected demand and safety stock are taken into account. So a release decision integrates the essential functions of production planning on a job to job basis. The authors proposed three different expressions for the *workload smoothing value* and left the choice as a topic of further research.

Melnyk *et al.* (1991) examined, through a computer simulation of a random job shop, how smoothing by the planning system can improve system performance and enhance the effects of ORR. The authors tested the system with Poisson input when each job was assigned a due date on its arrival which is equal to the sum of its arrival time and its weighted total estimated work content. Smoothing was done by defining a maximum and a minimum amount of work that the planning system is allowed to send to the shop floor in each planning period. The closer these two limits are, the smoother is the input of work to the shop. This amount of work was then released to the shop or was temporarily held back in the order release pool by the existing order release mechanism for further smoothing of load on the shop floor. The "filtering" mechanisms of the planning system smoothing and ORR have a complementary impact on the system, with smoothing working to reduce flow time and flow time variability and ORR working to reduce WIP and WIP variability. The combination of smoothing with ORR, results in shorter and more consistent lead times, lower and more stable WIP levels and better delivery performance, which results in a very stable and predictable system. The study also shows that the combined effect of smoothing and ORR can improve the performance of simple shop floor dispatching rules like first-come-first-served to the point where they are competitive with more sophisticated, due date-oriented rules.

(d) ORR by controlling the workload on the bottleneck machine

A number of researchers have considered the release of orders by examining the condition of bottleneck machines.

Glassey and Resende (1988) introduced a bottleneck order release strategy which seeks to avoid starving bottleneck machines by ensuring release of jobs as the work content for the bottleneck falls below certain levels. It had the objective of high bottleneck utilization and low inventory. They tested several combinations of release and dispatch policies and found their release algorithm to perform the best.

Wein (1988) tested IMR (with Poisson and deterministic inter-arrival times), closed loop input, and workload regulating input in combination with fourteen lot sequencing rules for several different models of a wafer fab. In the case of closed loop input, the number of lots in the system is kept constant, whereas in the case of workload regulating input, a lot is released into the system whenever the total amount of remaining work in the system for any bottleneck station falls below a prescribed level. Results show that scheduling has a significant impact, with larger improvements coming from discretionary input control than from lot sequencing rules. Workload regulating inputs performed the best. He concluded that in an environment where control over inputs can be exercised, the biggest improvements can be achieved through input control.

Roderick *et al.* (1992) studied the concept of operating a factory at constant WIP. They considered random processing times with various shop sizes and orders having similar and dissimilar routings. The authors investigated four order release strategies, of which the first two were a constant WIP order release strategy and a bottleneck strategy, which were developed with the help of characteristic curves, defining the relationship between WIP and the rate of production. The bottleneck strategy was similar to the "starvation avoidance" policy of Glassey and Resende (1988). The third strategy matched order release to those orders completing production over prior time periods and the fourth strategy fixed order release at a desired level of production output. Among these four the constant WIP and the bottleneck strategy performed better under a wide variety of shop conditions, although the bottleneck strategy could never outperform the constant WIP strategy.

Philipoom *et al.* (1993) investigated the performance of capacity-sensitive ORR procedures in job shop environments. The authors proposed a capacity sensitive ORR procedure called path-based bottleneck (PBB) and compared it with modified infinite loading (MIL). Their PBB procedure is based on limiting the flow of work to those machines which are capacity constrained, and likely to become bottlenecks in the near future. Results showed that PBB worked well in lowering total costs when the due date was tight, while MIL was a better procedure with relatively loose to medium due dates tightness.

A similar conceptual approach was also implemented by Melnyk and Ragatz (1989) with their WCEDD and AGGWNQ models, as mentioned earlier.

(e) ORR by controlling the arrival process

There has been some research where the arrival process itself is controlled by deciding if an incoming order from the customer will be accepted or rejected. Since a manufacturing system can be well represented as a queuing system, the research in queuing theory is relevant in the case of manufacturing systems. Models from queuing theory are now widely recognized as useful aids toward understanding and controlling congestion while maintaining throughput in many production, service and transportation system.

In a bibliography of research on optimal design and control of queues, Crabill *et al.* (1977) listed a wide variety of research in queuing theory spanning across six broad categories. In this paper, five types of possible control of the arrival process are mentioned which are as follow:

(i) A facility exercising an extreme control of accepting or rejecting customers. This amounts to changing the arrival rate from its normal level (accept) to level zero (reject).

(ii) A facility exercising an intermediate control on the arrival process (*e.g.* by altering the mean arrival rate), with all customers accepted.

(iii) Customers themselves making the decision of accepting or rejecting the entry to the queue (by reacting to certain pricing policy or tolls or to estimates of system congestion).

(iv) Customers optimizing their own individual objectives against optimizing social or group goals. In this category, research attempts to develop a pricing mechanism that induces customers to act in a socially optimal manner.

(v) Controlling the decision when a system should no longer accept customers *i.e.* when to "close down" operation.

The authors cited several references for the extreme type of control as mentioned *viz.* Lippman (1975), Lippman and Ross (1971), Miller (1969), Scott (1969, 1970).

In a more recent study, Stidham (1985) also reviewed the research on optimal control of admission to a queue. He reviewed both static (open-loop) and dynamic (closed-loop) models for control of admission to a queuing system. The main emphasis was on the difference between socially optimal and individually optimal controls.

All of this research work on controlling the admission into queue(s) involves simple analytical studies and is unable to handle the complexity of real manufacturing systems. On the experimental side, Wester *et al.* (1992), ten Kate (1994) and Philipoom and Fry (1992) report simulation-based research on arrival process control. This research was motivated by the inadequacy of the delayed order release strategy to improve delivery performance in make-to-order manufacturing systems. The experimental researchers in the area of WLC have realized only relatively recently the importance of controlling the arrival process itself. In fact, they did this as a last resort, only after thoroughly examining the constrained order release strategy (while accepting all orders), because rejecting an order means certainly losing the possible profit from the order and possibly tarnishing the manufacturer's goodwill. They understood that rejecting some orders is the only solution in a make-to-order environment where capacity is fixed and due dates of orders cannot be manipulated.

Wester *et al.* (1992) experimented with a make-to-order multi-product single machine manufacturing system to study the interdependence between order acceptance, production planning and scheduling. The authors investigated the level of information needed as a basis for a good acceptance decision. They explored three basic approaches to accept an order. In the *monolithic* approach, the acceptance decision is based on detailed information on a current production schedule for all formerly accepted orders. In the *hierarchic* approach, the acceptance strategy is based on a global capacity load profile only, while detailed scheduling of accepted orders takes place at a lower level. In the *myopic* approach the acceptance decision is similar to the one in the hierarchic approach, but the scheduling is myopic in the sense that once the machine becomes idle only the next order to be produced is actually scheduled. The experiment showed that the differences between the performance of these three approaches are small. The slightly better performance of the monolithic approach was due to the selective acceptance mechanism implicitly present in the case of a heavy workload.

ten Kate (1994) compared two coordination mechanisms between production and sales activities *viz.* a ***hierarchical approach*** and an ***integrated approach***. In the ***hierarchical approach*** the scheduling function and the order acceptance approach are separated and the only information which is shared is the aggregate information on the workload. The decision whether or not to accept an order is based on aggregate characteristics of the set of already accepted orders. The production schedule is periodically updated for the orders accepted recently. In the *integrated approach* order acceptance and production scheduling are integrated. The decision whether or not to accept an order is taken by determining a good production schedule which includes the new order. The researcher compared both the approaches in an experimental setting and concluded that for most of the situations there is relatively little difference between the two approaches. Only for severe situations *i.e.* short lead times, high utilization rate, does the integrated approach outperform the hierarchical approach.

Philipoom and Fry (1992) studied capacity-based ORR strategies. They simulated a manufacturing facility which was a hybrid job-shop comprised of twelve machines grouped into five work centers. In this research, the assumption that all orders received by a shop will in fact be accepted was relaxed. Three methods to determine whether or not to accept an order were tested in this research. Results suggested that consideration of shop loads was better than random rejection in determining whether an order should be accepted or rejected by the shop. The experiment showed that rejecting a small percentage of the arriving work can result in dramatic improvements in shop performance. The study also suggests that an order review methodology based on path loads is more effective than one based on aggregate load in the entire shop.

Wouters (1997), also makes a contribution in this area by discussing the economic considerations for order acceptance. Only those costs are relevant in order acceptance, which would be avoidable if the order is not accepted (incremental costs plus opportunity costs). The author noted that in practice it is difficult to apply the concepts of relevant costs to practical order acceptance decisions. The production planning and control function can provide some of the information that is required for calculating the relevant costs involved in a particular order acceptance decision. This information concerns capacity cost behavior (to calculate incremental costs) and planned capacity utilization (to calculate opportunity costs). Moreover, the author suggests that to assess the reliability of these calculations, the information on planned versus actual capacity utilization, planned versus actual cost behavior and on the variation of contribution margins can help.

(f) ORR viewed as a step towards JIT

Some researchers have viewed ORR as a step towards implementing JIT. Among them Spearman *et al.* (1990), Lingayat *et al.* (1991), Spearman and Zazanis (1992) deserve mention.

Spearman *et al.* (1990) proposed a 'hybrid' push/pull system that would maintain constant WIP. Jobs are pulled into the system by the completion of any job and are pushed from one machine to another, which creates a constant WIP system.

Lingayat *et al.* (1991) pointed out that an order release mechanism provides a simple method of implementing a near pull system by controlling the flow of raw material. The characteristic of the order release mechanism *viz.* to hold on to the orders in the form of raw materials until needed by someone down the line, is a feature similar to a JIT system. The only difference is releases are controlled only at the raw material stage. The authors supported their view by a simulation study of a flexible multi-product flow system in a make-to-order environment. They developed an order release mechanism which released a set of successive jobs in the order release pool starting from the head of the pool, whenever the total workload of orders in the set reached a desired value. This value was defined as the minimum operation load for a particular batch process of the system. The orders in the order release pool were arranged in a non-increasing order of their workloads. It was also ensured that an order is not held back for more than a specified amount of time. The results showed that the mean time spent on the shop floor and its standard deviation were significantly less when using their order release mechanism. Also the maximum time spent on the shop floor was at least 50% less. However, the total time in the system went up for some order types.

Spearman and Zazanis (1992) compared a "pull" system with a "push" system and commented that the pull system is better because the pull system produces less congestion and it is easier to control. Also, the benefits of a pull environment owe more to the fact that WIP is bounded than to the practice of "pulling" everywhere. They also identified a hybrid control strategy called "CONWIP", that has push and pull characteristics and outperforms both pure push and pure pull systems.

(g) ORR by controlling the output

Controlling the lead time can be achieved in yet another way *i.e.* through the control of shop production capacity. Hendry and Kingsman (1991) implemented a control system in which input, in terms of orders released to the shop, and output, in terms of capacity, are controlled at the same time.

Onur and Fabrycky (1987) presented a combined input/output control system for periodically determining the set of jobs to be released and the capacities of processing centres in a dynamic job shop, so that a composite cost function is minimized. An interactive heuristic optimization algorithm incorporating a mixed integer program was formulated. The resulting control system was compared by simulation with an alternate system for which only the input was subject to control. Results showed that significant improvements were achieved in the overall performance (in terms of *cost*) under high shop congestion, but not in the situation when the shop was lightly loaded. Significant improvements were also achieved for the mean flow time, flow time variance, mean tardiness, tardiness variance, and WIP inventory levels.

Hendry and Wong (1994) examined three order release rules. Two of the mechanisms assume that the set of jobs to be released is given and the capacity of the resources cannot be adjusted, while the third rule can adjust capacity as soon as new jobs are entered into the system and released to the shop floor. Their simulation study showed that the latter rule is the best one under delivery performance and workload measures, but does not do so well under a workload balance measure.

Lingayat *et al.* (1995) reported on an order release mechanism applied to a flexible manufacturing system. Here the rule not only decides which order to release and when to release it, but also determines the routing of the order. This mechanism has been compared to the CONWIP approach, and they found that the mechanism in question not only improves the mean shop flow time under all load conditions, but also reduces the variance of this measure. The system flow time also decreases at high load levels. They suggested that the choice of an order release mechanism is more important than the choice of a dispatching rule.

(h) Criticism against ORR

The ORR approach is not free of criticism and its positive impact has been challenged by several researchers.

Input control certainly reduces the *manufacturing* lead time (*i.e.* the time the job actually spends on the shop floor) of a job, but as Melnyk and Ragatz (1989) found, this reduction may be more than offset by the time spent in the order release pool, which is a pre-shop queue. So the introduction of order release mechanisms might not reduce *customer order* lead time or system flow time (*i.e.* the time the order spends in the system from its acceptance until it exits from the system), but rather it might shift the queue time from the shop to the order release pool.

Moreover, as Baker (1984) noted, although input control streamlines the flow of work on the shop floor and makes scheduling easier, it also may make scheduling less effective. In particular, any scheme that restricts the set of jobs available for scheduling will remove some options that would otherwise be available. At the margin, this kind of restriction can cause some deterioration in schedule performance. He experimented with a simplified single machine simulation model and presented a three-part control system consisting of due date assignment, order releasing decision, and dispatching decision. The results showed that modified due-date priorities perform more effectively than other priority rules when performance is measured by average tardiness. Moreover, the experiments indicate that performance under the modified due-date is not improved by the use of input control. On the contrary, with dispatching rules that rely on shortest-first or critical ratio properties, the experiments indicate that input control is not always advantageous.

Bertrand (1983a, 1983b) has reinforced this criticism by showing that some ORR techniques can lead to long delays in the pre-shop pool such that the overall system flow time may be increased for some orders.

Kanet (1988) also examined the performance of a shop floor with load-limited order release such that whenever the inventory of work at a work center exceeds some critical value, further release of orders which are routed to that work center is prohibited. After the inventory is processed, release of work to the shop is again allowed. The author reported a comparison between analytical results for an M/M/1 queuing model, along with existing simulation studies of multi-machine job shops. Results showed that system flow time, inventory, and tardiness all deteriorate to the extent that load limits introduce idle time into the schedule. The author advised caution when implementing input control at any work center other than a gateway station (*i.e.* the first station on the route of an order). He concluded that, while ORR may reduce the time an order spends on the shop floor, it might not reduce the overall system flow time, when the waiting time in the order release pool is also counted. He also commented that the usage of ORR strategies, implemented to reduce the customer delivery time, might have the opposite effect.

The fact that the overall system flow time cannot be reduced by the ORR mechanism alone, has also been supported by Melnyk and Ragatz (1988) and by Melnyk *et al.* (1994b).

Melnyk *et al.* (1994b) tried to resolve this dilemma around ORR by defining the applicability and role of ORR techniques. They concluded that:

> "The performance of an ORR system is strongly dependent on the presence of variance control at both the planning and the shop floor level. One way of understanding the activity of an ORR mechanism is simply as a filter and a fine-tuning mechanism which essentially decouples the planning system from the shop floor and its performance."

Fredendall and Melnyk (1995) tried to further clarify whether or not ORR mechanisms can be of benefit. They reported in their study that:

> "ORR systems do reduce the variance of performance measures, and they do have a direct impact on system performance. However they are not the dominant variables in the shop. Rather, they modify the performance of the planning system that ultimately generates the schedules. As a result, their performance is highly dependent on the performance of the planning system. As such, ORR mechanisms can be best described as being partial mediating variables. Consequently, ORR mechanisms should not be viewed in isolation from the planning environment in which they are used."

Thus, if the order release pool is exposed to high variability of workload, ORR cannot release all of the work and waiting time in the order release pool increases. Similarly when the variance of the shop floor is high, ORR becomes overwhelmed. This suggests that there may be a specific range of variance within which ORR works effectively.

2.5 Motivation for the Present Research

In recent years, academicians and researchers in the area of manufacturing system control have been able to identify more controllable variables than ever before.

> "For example, with the advent of better capacity planning systems such as Capacity Requirement Planning (CRP), we can influence the loads released to the shop by identifying and managing any peaks and valleys in the load. We can also affect the rate and mix of work released to the shop floor through the use of Order Review/Release (ORR). Finally, we can also reduce the variability in process times on the shop floor through the use of techniques such as Single Minute Exchange of Dies (SMED) (Shingo, 1985) and Just-In-Time Manufacturing (JIT) practices." (Melnyk *et al.*, 1994b)

In earlier times, these variables were thought to be beyond the control of management and hence the freedom to manipulate the activities of both the planning and control of the manufacturing system was restricted. As Eilon *et al.* (1975) pointed out, " If the arrival of jobs, their processing requirements, and the operating facilities are given, the only control parameter at the disposal of the scheduler is ... the order in which the job should be processed." The growing awareness regarding these broader control options has produced a large number of research papers concerning different aspects of delayed and judicious order release in the last two decades. But this obviously did not solve the problem except providing partial benefits as mentioned in section 2.3.

As pointed out by Melnyk *et al.* (1994b) and as has been already mentioned in the previous section, the incapability of the order release mechanism *alone* to reduce the system flow time makes it necessary to have a good planning system which feeds orders into the order release pool with low variability. If the order release mechanism is exposed to the external dynamics of order arrivals then the order release pool will most likely be overloaded at times by the incoming orders, since the orders are going to wait for release due to capacity shortage during that time period. However sophisticated the order release rule may be, the order release pool will not be able to release the waiting orders unless the required capacity is again available. This will make the system flow time no better. Hence it seems that the concept of careful acceptance or rejection of orders is the only solution in make-to-order manufacturing environments where capacity and due date (*i.e.* flow allowance) are fixed. The barrier of acceptance or rejection might serve here as a filter to the manufacturing system, which is expected to reduce the variability.

The importance of controlling orders at the entry to the shop floor has already been recognized in the research literature. As has been pointed out earlier, in queuing theory research the concept of controlling the arrival process has been around since 1969 while on the experimental side, Philipoom and Fry (1992), ten Kate (1994) and Wester *et al.* (1992) are the only three published research work so far in this area. There is a clear gap and scarcity of research regarding this. Controlled acceptance needs to be studied in the context of more complex experimental settings (unlike the simplistic settings of queuing theory research) and deserves closer attention regarding how this control should be adjusted depending on various uncontrollable environmental factors under which the manufacturing system is operating so that the maximum benefit can be achieved. This will provide a manager the necessary understanding and insight to manipulate the control relative to the dynamics of uncontrollable factors to achieve the best possible benefit for that circumstance. Studying what should be the suitable choice of control policy under a given circumstance was absent in any of the experimental research done before. Both of Philipoom and Fry (1992) and Wester *et al.* (1992), in one or more of their order acceptance strategies, accepted an order only if the workload (which is defined in some fashion) is not more than a maximum limit. In their research they did not study how to choose this control limit to suit a given set of values for the uncontrollable factors. This present research is motivated and focused towards this direction.

Apart from this, several researchers have already flagged the possibility of further research involving accepting or rejecting an order. Among them, Land and Gaalman (1996), Malhotra *et al.* (1994) and Jensen *et al.* (1995) are the noted ones. Land and Gaalman (1996) observed the importance of keeping the order release pool size stationary. The authors noted that, "Existing WLC-concepts confronted with strong dynamics of the incoming stream of orders will depend on either high flexibility of capacity or possibilities to reject stationarity disturbing orders at the entry level." On the other hand, Malhotra *et al.* (1994) and Jensen *et al.* (1995) advocated further research to selectively accept the normal priority orders, while managing a two-class order system.

The situation of multiple order classes has not been studied, when some form of input control is operative. When input control mechanisms are used in a situation of multiple order classes with orders having differences in importance, a great deal of opportunity exists to control the manufacturing system through selective acceptance of orders to manipulate the service level of different classes of order.

2.6 Objective of the Research

The objectives of the present research stem from the motivation as stated in the previous section. More specifically, the objectives of the research are as follows:

(i) To explore in detail the behaviour of two alternative algorithmic accept/reject rules in order to both gain insight into the basic operation of systems where the rejection of orders is allowed and to quantify how the performance of such rules is affected by certain key factors in the environment of the wider manufacturing system.

(ii) To compare the performance of a new simulation-based accept/reject rule with the two algorithmic rules to identify under what, if any, circumstances this rule may outperform the others.

The applicability of simulation in the area of manufacturing systems analysis is well-known since it can handle complex stochastic systems in arbitrary detail. As Grant (1988) pointed out, "Historically, simulation techniques have been highly successful and used extensively for the planning and analysis of current operations and proposed designs." From the literature review in the earlier section, it is clear that there has not been any research so far which uses this capability of simulation in deciding the acceptance of the customer order. This justifies the implementation and testing of a simulation-based order acceptance strategy.

(iii) To investigate the optimal choice of accept/reject rule, and of any control parameters of the chosen rule, as a function of the primary environmental factors of the wider manufacturing system.

This is another area where no work has been done so far. It is clear that the control parameters that work best in a particular situation will not necessarily be the best in a different situation, thus it is necessary that the parameters are chosen appropriately as a function of the environmental factors. In the previous literature, all the research works were carried out when the control parameters are chosen *once* under a particular situation and the manufacturing system was studied with the same value of the control parameter even when other factors of the manufacturing system were changed. So it is justified that there is a research need to explore how to choose these control parameters as a function of the specific manufacturing environment.

(iv) To explore the behaviour of the three implemented accept/reject rules in the case where there are two classes of order both to gain insight into the basic operation of systems able to reject jobs in this case and, again, to quantify the performance of the rules as the main environmental factors are varied. Of particular interest here is how the accept/reject rules perform differently for different classes of order.

As has been pointed out earlier, there exists a good deal of scope to manipulate the service of different orders varying in importance, by means of selective acceptance of orders. Malhotra *et al.* (1994) and Jensen *et al.* (1995) have suggested this possibility in their research. To study how the service of different classes of order is affected is useful in manipulating the service level offered to different order classes.

Chapter 3

Experimental Model

In the previous chapter the motivation for and objectives of this research have been presented. This chapter discusses the model which is experimented with in order to meet these objectives. First a hypothetical manufacturing system that has been used in this research as a test bed will be fully described, including the different underlying assumptions involved in the design of this system. Next, the alternative control policies, whose performance when applied to the manufacturing system under different operating conditions is of interest, are elaborated. Finally the important features of the simulation model developed to represent the hypothetical system will be described.

3.1 A Hypothetical Manufacturing System

For this research, a hypothetical manufacturing system has been designed as a test bed to explore various control policies under various operating conditions of the system. In this section, the following aspects of the system are described *viz.* (1) layout and job routings, (2) customer demand process, (3) order class, (4) due date assignment, (5) cost structure, (6) different decision points.

3.1.1 Layout and Job Routings

The hypothetical manufacturing system, which operates continuously, has four work centres as shown in the **Figure 3.1**. The first, second, third and fourth work centres have 2, 3, 2 and 3 machines respectively. Each machine is different from the other machines in the system (although there are some similarities between the machines within a work centre).

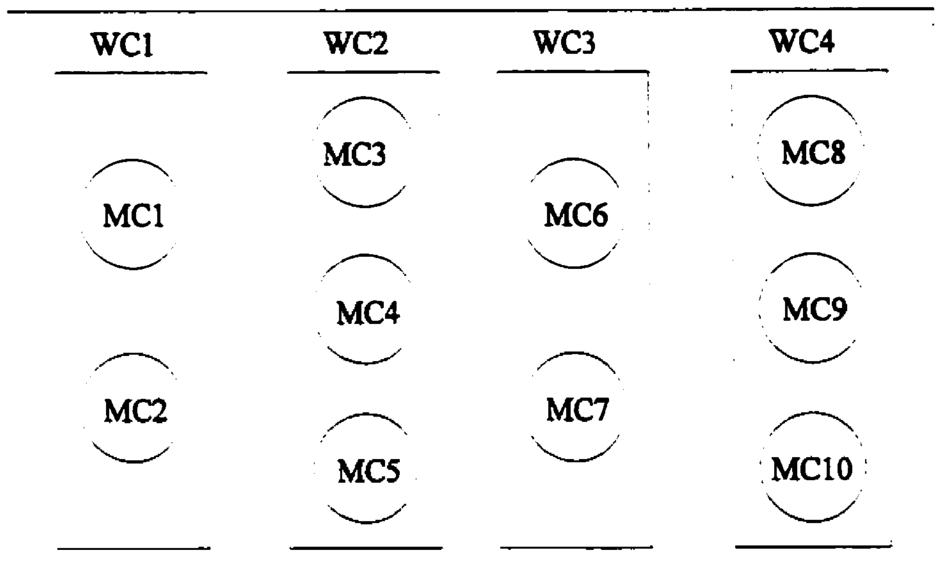

Figure 3.1: The Layout of the Manufacturing System

A job is processed in the system under the restriction that, at any step if the job is processed at a work centre i, then in the next step it can be processed at a work centre j, only if $j>i$, where $1 \le i \le 4$, $1 \le j \le 4$. Thus a job cannot be processed by any machine at a work centre if it has been already processed by another machine in the same work centre, or it cannot be processed by any machine in a work centre if the numerical value of that work centre is less than that of its previous work centre. Also, it might have any number of operations from one to four and obviously it can skip one or more work centres. Thus it is possible to generate at most 143 different job routes, each giving rise to a unique job type. In this research all 143 different possible job types have been considered. For a particular job type, the sequence of machines that will be visited by the job and also the processing time on each of the machines is known beforehand. The exact process plan for each job type is defined in the input file shown in the **Appendix B**. The processing times of the machines in the work centres 1, 2, 3 and 4 are drawn from a Gamma distribution with the mean processing times as 2.5 hours, 3.5 hours, 2.5 hours and 3.5 hours respectively. The process times being drawn from Gamma distributions enables the coefficient of variation of the process times to be easily controlled during experimentation.

The layout of this manufacturing system is similar to the one considered in Philipoom and Fry (1992). The justification for considering this type of layout, as given by the above authors, also holds good in the present case. In this layout the machines of similar function are grouped in the same work centre. This does not necessarily mean that the machines in the same work centre are identical, rather they are of same kind but of different capacities. For example, two shaping machines of different capacities can be placed in the same work centre and a job which is processed by one of those two machines does not need to go through the second one again. Thus each machine is assumed to be different. The work centres are also arranged according to their functional or technological precedence. So in this kind of shop all jobs will have a unidirectional flow. As the authors say, "In the 'real world', it is doubtful that a pure job-shop exists where a job can begin and end in any department. Indeed there is usually a dominant product flow that characterizes the manufacturing process." This hypothetical hybrid job shop is representative of this kind of manufacturing environment.

There are two differences, however, between the manufacturing system of Philipoom and Fry (1992) and the present one in this thesis. In the previous one, the authors have considered five work centres and all jobs have five steps *i.e.* they are processed in all five work centres. In the present manufacturing system there are four work centres and the jobs can involve any number of steps between one and four.

3.1.2 Customer Demand Process

The demand on the system is characterized by the orders placed by the external customers. The manufacturing system under consideration is operated on a strict make-to-order (MTO) basis, so all the demand that the manufacturing system faces is external in nature.

In this research, it has been assumed that the customer orders arrive in a batch size of unity. The problem of non-unity and/or nonuniform batch size is a topic suitable for further study. All possible job types and hence the resulting job routes (given earlier comments on shop structure and job routings) are equally probable. The inter-arrival time (IAT) between two consecutive orders is distributed according to a Gamma distribution, enabling a fine control over both the mean and coefficient of variation of the inter-arrival time distribution. In this research, IAT is manipulated to vary the expected demand level (*i.e.* the steady-state shop utilization corresponding to no job rejection) and hence, the parameters of the inter-arrival time distribution will also change accordingly.

3.1.2.1 Justification of Choosing an MTO System

The reason why a MTO system has been chosen is as follows. The hypothesis that rejection of a small portion of incoming orders improves delivery performance may be true in both make-to-order and make-to-stock (MTS) manufacturing systems. Exploring the effect of rejecting some of the orders in the MTS case where customer orders can be delivered directly from the manufacturing shop floor or from a finished good inventory, is more complex than that in the MTO case, the finished good inventory not being an option in the latter case. Thus the knowledge gained from the MTO research will help tackling the problem in the MTS case.

3.1.2.2 How is a Customer Enquiry Addressed in an MTO System?

At this point, it is helpful to briefly describe how a typical MTO manufacturer responds to customer enquiries. For additional detail please refer to Kingsman *et al.* (1996). A typical MTO manufacturer deals with a customer enquiry basically in four stages. The first stage is an initial evaluation to determine whether the manufacturer wishes to make a bid for the order. The outcomes of this stage are the decisions to prepare or refuse a bid, and possibly to seek further clarification on the request if it accepts the bid. In the second stage, the manufacturer decides how the cost estimates will be prepared. This means specifying how much time should be spent in the estimation process. The third stage is the process of preparing the cost estimates themselves. This includes specifying and configuring in detail how the job will be made and also deciding upon material and process plan of the job. The final stage is to set the price and lead time to bid. Here the question is to decide the margin of profit to attach to the cost estimate. After these four stages, the proposal is put to the customer, who may accept it, reject it, or may ask for further negotiations. A further negotiation may just be a request for a lower price or could be a joint exploration of ways to change the specification to reduce the cost. Another possibility on behalf of the customer is to ask the manufacturer for a new price for a specific delivery date, different to the one proposed by the MTO manufacturer.

From the above description, it is evident that, as the manufacturer might refuse to bid in the very first stage, similarly the customer also might refuse to accept the manufacturer's proposal of estimated cost and delivery date. However, in this research it is assumed that a customer, when placing an order, always accepts the proposal of the manufacturer. It is the manufacturer who might occasionally reject the order, as will be explained in detail in a later section. Moreover as compared to the real situation as described, in the present thesis every order has a fixed price depending on its type and class. Also, each order has a standard flow allowance based on its class. The decision whether the order will be accepted or not, is taken immediately after the arrival of the order. No further negotiation, on price or due date, is considered in the current research.

3.1.3 Order Class

In some of the planned experiments two different classes of order have been considered. A certain percentage of incoming orders are considered to be "urgent", with the remainder being "regular" orders. From the point of view of simplicity, only two classes of orders have been considered in this research. Whether an order is urgent or regular is determined by the customer. An urgent order is distinguished from a regular order by its relatively shorter standard flow time allowance at the time of assigning its due date. The percentage of urgent orders is a controllable parameter in this research.

3.1.4 Due Date Assignment

When the orders are generated from the external customers, each order is given a due time according to the following due time setting rule:

$DT_i = AT_i + RegFTA$, if the order is in question is a "regular" class order, or
$DT_i = AT_i + UrgFTA$, if the order is in question is an "urgent" class order.

Where,	DT_i	=	Due time of the *i*th order.
	AT_i	=	Time of arrival of the order into the system.
	$RegFTA$	=	A constant.
	$UrgFTA$	=	A constant (such that $RegFTA > UrgFTA$).

There are numerous alternative ways to assign the due date to the incoming job and a vast literature on this particular subject is readily available. The due date assignment by adding a constant flow time allowance to the arrival time as above is one of the simplest due date assignment rules. Although this rule cannot claim superiority over or is not at par with other rules which use the load information on the shop floor or the order itself, many companies in real life still use this rule for the sake of simplicity. Moreover, this rule provides a good deal of certainty from the point of view of the customer. However in this research, the primary reason for the choice of this rule is its simplicity.

3.1.5 Cost Structure

According to Enns (1995), profit for an order can be defined by the following expression:

Profit (PFT) = Revenue (Rev) - Variable production cost (VC)
- WIP holding cost (HC)
- Lead time cost (LC)
- Due date deviation cost (DC)
- Fixed overhead cost per order (OH) (3.1)

Revenue (Rev) of an order is the amount of dollars earned after a finished order is shipped to the customer.

Variable production cost (VC) of an order is the amount of dollars spent in completing the order. This cost includes material and labour costs.

WIP holding cost (HC) is the total cost incurred for holding a finished or semifinished order in inventory for a duration. Any extra storage, handling, insurance and obsolescence charges associated with the work-in-process inventory should be included in this category of cost.

Lead time cost (LC) expresses the loss in revenue or customer goodwill which results from lead time quotations which are longer than those desired by the customer. This loss is often intangible.

Due date deviation cost (DC) reflects costs attributable to the difference between the actual completion time and the due date. The main components of this costs are earliness and tardiness costs. In this research, the earliness cost (EC) is assumed to be zero and hence DC is composed of only the tardiness cost (TC).

Fixed overhead cost (OH) is a constant which includes the cost to maintain the facility and other indirect costs.

In this research the general expression of the profit in the equation (3.1) has been modified in the following way. In this case, VC, HC, LC and OH have been assumed to be fixed for simplicity. DC has been considered to include only the tardiness cost (TC) *i.e.* the earliness cost is zero, again to simplify the scenario. However, more detailed modelling of the other cost components (at least VC, HC and EC) is a potential research problem of the future.

So in this research, the equation (3.1) takes the following simple form in which **Rev** is the revenue after VC, HC, LC and OH are deducted.

$$\mathbf{PFT = Rev - TC} \tag{3.2}$$

3.1.5.1 Formulation of Revenue

Revenue is calculated for an order according to the following expression.

$Rev_i = [Kr \times TWK_i]$, if the order is a "regular" one, and (3.3a)

$Rev_i = [Ku \times TWK_i]$, if the order is an "urgent" one. (3.3b)

Where,	Rev_i	=	Revenue (as defined in (3.2)) for the *i*th order.
	Kr	=	A positive constant.
	Ku	=	A constant (such that $Ku > Kr$).
	TWK_i	=	Total estimated work content of the *i*th order.

3.1.5.2 Formulation of Tardiness Cost and its Justification

The tardiness cost in general, can be characterized in many different ways. It could be linear, nonlinear, or even constant and independent of time. Also, it could be uniform or nonuniform across different jobs. For instance, Alidee (1994), Arkin and Roundy (1994), and Szwarc and Liu (1993) specified the tardiness cost as proportional to a job's processing time. According to these authors, it is highly undesirable for job completion times to deviate from their due date for large jobs, and that it is not logical to use uniform tardiness costs for jobs with varying sizes. Holt (1963) advocated that it is more realistic to consider the tardiness cost function to be nonlinear over time. Heady and Zhu (1998) summarized the approaches reported in the literature as follows:

> "There are three penalty cost functions commonly assumed in the literature. First, the penalty cost is proportional to the length of a job's processing time. The justification for this cost function is that the longer it takes to process a job, the more value the job possesses. Therefore, both earliness and tardiness on that job should be heavily penalized. Second, the penalty cost function is linear in the number of time units that a job is early or late. This alternative severely penalizes those jobs that deviate far from their due dates in either direction. Third, the uniform cost function alternative equally treats jobs that are early or late regardless of severity of their earliness or tardiness."

In this research, if an order becomes tardy, the resulting tardiness cost is proportional to the product of its revenue (from equation 3.2) and its tardiness. In the light of the above literature, this scheme seems to be reasonable. However, to keep the design less complicated the tardiness cost has been chosen to be linear over time against its nonlinear counterpart. The exact formulation is as follows:

$TC_i = Ktr \times Rev_i \times Tardiness$, if the order is a regular one and, (3.4a)

$TC_i = Ktu \times Rev_i \times Tardiness$, if the order is an urgent one. (3.4b)

Where,	TC_i	=	Tardiness cost of *i*th order in question.
	Ktr	=	A positive constant.
	Ktu	=	$Ktr \times \frac{RegFTA}{UrgFTA}$
	Rev_i	=	Net revenue for the *i*th order in question (before considering tardiness costs)
	$Tardiness$	=	Amount of tardiness on completion (which is zero or a positive quantity).

In the following **Figure 3.2**, this tardiness cost (TC) curve has been illustrated with respect to the flow time of a job. *A* is the arrival time and *D* is the due date of the job, while *AD* is

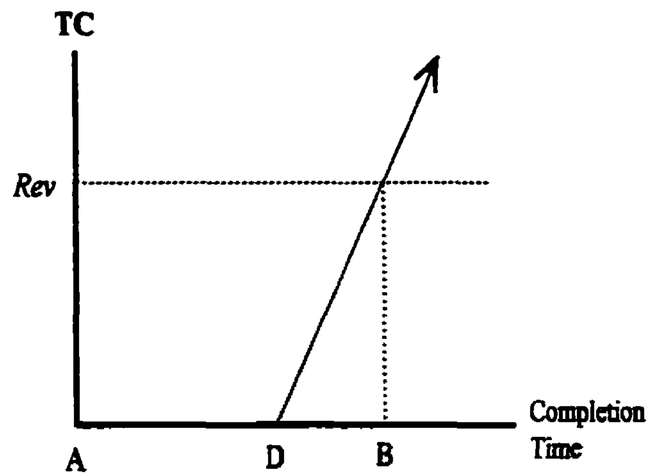

Figure 3.2: Tardiness Cost Curve

its flow time allowance. If the completion time of the job extends beyond its due date, the tardiness cost accumulates linearly until the date of completion. If the job is tardy by a duration equal to *DB*, all of the job's net revenue is offset by tardiness cost. This specific value of tardiness can be called the *Critical Tardiness* (T_c). It is interesting to note that T_c is independent of job type for each class of order, but it certainly depends on the job class. As it is evident from the equations (3.4a) and (3.4b) T_c equals *1/Ktr* or *1/Ktu* depending on whether the job is a regular or an urgent one.

Another interesting point concerning critical tardiness can be made by comparing it with the flow time allowance. The ratio of critical tardiness and flow allowance indicates how heavily a job will be penalized if it is tardy by its flow time. Obviously, this ratio is *(1/Ktr)/RegFTA* or, *(1/Ktu)/UrgFTA*, depending on whether the job is a regular or an urgent one. In this research, the value of *Ktu* has been chosen so that the two order classes are penalized equally heavily from a *relative* tardiness perspective, *i.e.* if each class is tardy by its flow allowance it will incur a penalty equal to the same proportion of its net revenue. Thus,

$$Ktu = Ktr \times \frac{RegFTA}{UrgFTA}.$$

3.1.6 Different Decision Points

While the manufacturing system is in operation, three kinds of decision are taken at different points: (i) *Accept/reject decision*; (ii) *Order release decision*; and (iii) *Dispatching decision*. A control system assists the main system to take these decisions as and when necessary. **Figure 3.3** is a schematic diagram showing the overall decision-making process. This section provides a brief introduction to each of these decisions. A further detailed discussion of different alternatives for each decision will be provided in section 3.2, while describing different alternative control policies.

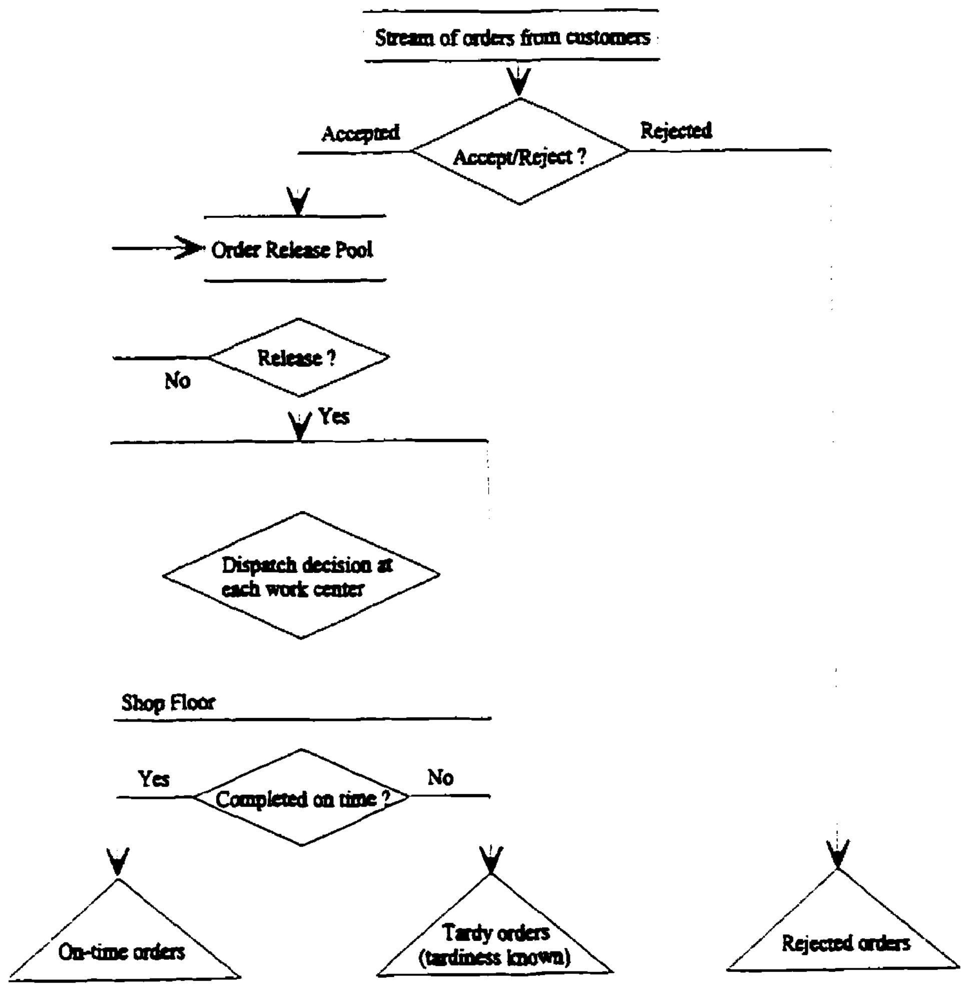

Figure 3.3: Schematic Diagram of the Overall Decision-making Process

3.1.6.1 Accept/Reject Decision

The first decision is taken when a customer attempts to place an order, with the manufacturer deciding whether or not to accept the order, depending on a particular accept/reject rule. As was pointed out earlier in section 3.1.2.2, in this research it has been assumed that a customer when placing an order never withdraws that order unless it is rejected by the manufacturer. The orders which are rejected are lost forever *i.e.* the rejected orders are not considered again in the future and it is assumed that they find other suitable manufacturers. However, there are many other conceptually different ways possible, in which this accept/reject decision might be accomplished. **Appendix C** discusses these strategic alternatives and it is to be noted that each of these strategic alternatives can be fleshed out again into a number of different rules which are more concrete in nature.

3.1.6.2 Order Release Decision

The orders which are accepted are temporarily kept in a pre-shop pool known as the "Order Release Pool". This second decision is necessary to decide which of the accepted orders will be released from the pre-shop pool and what is the most appropriate release time for the order. This decision is taken on the basis of an order release rule. Orders may be released at any time and in any number, if permitted by the order release rule.

As in the case of accept/reject rules, conceptually many different ways are possible again, to decide on this issue. A survey of different alternatives has been already done by a number of authors and has been reported in the previous chapter in detail.

3.1.6.3 Dispatching Decision

The last decision in the system is taken regarding which order in a machine's queue will be processed next, if there is more than one order waiting in the queue and the machine is free.

3.2 Different Alternative Control Policies Used in This Research

In this section, the different alternative control policies implemented in the model will be described. To support this description, the next section defines some important quantities made use of within the alternatives (specifically in the accept/reject rules and the order release rules) including information on the time and the way they are updated. Also, for clarity of description in the very beginning, it is useful to clearly distinguish among three different terms *viz.* an *order*, a *job* and a *task*. So far any two of these terms might have been used interchangeably, but from now onward they will be used strictly in the sense as they are defined below.

When a request is accepted from the customer and placed in the order release pool, it is referred to as an *order* as long as it is in the order release pool. When an *order* is released to the shop floor, it is referred to as a *job* and a *job* needs to undergo one or more operations by one or more machines in the shop. Each such operation is known as a *task*.

3.2.1 Important Quantities Involved in Different Rules

- *TotAcceptedL:*

  The total amount of estimated remaining work content of all accepted orders and jobs which are in the system at this moment.

  It is incremented just after accepting an order by an amount equal to the total estimated processing time of the order. Each time a machine starts a task, it is decremented by half of the task's estimated processing time, and is decremented by the remaining half immediately the machine finishes the task.

- *AcceptedLoadOnMc(i):*

  This is defined for each machine *i* as the portion of *TotAcceptedL* which must be performed at that machine.

  When an order is accepted the *AcceptedLoadOnMc(i)* for each machine *i* visited is incremented by the expected task processing time on that machine. When a machine either starts or finishes a task, this quantity is decremented by half of the estimated processing time of the task.

- *AcceptedLOR(j):*

  This is defined, for each order type *j*, as the subset of *TotAcceptedL* which must be performed on a subset of the set of machines in the facility which includes only those machines which an order of type *j* under consideration for acceptance would visit.

  This quantity is computed, whenever it is needed to support an accept/reject decision, by summing certain dynamically updated *AcceptedLoadOnMc(i)* values.

- *TotReleasedL:*

  This is defined as the total amount of estimated remaining work content of all the jobs in the system at this moment.

  This quantity is incremented whenever an order is released to the shop floor, by an amount equal to the total estimated work content of the order. This quantity is decremented whenever a machine either starts or finishes a task by an amount equal to half of the estimated processing time of the task.

- *ReleasedLoadOnMc(i):*

  This is defined, for each machine *i*, as the portion of *TotReleasedL* which must be performed at machine *i*.

  When an order is released the *ReleasedLoadOnMc(i)*, for each machine *i* visited, is incremented by an amount equal to the estimated task processing time on that machine. When a machine either starts or finishes a task, this quantity is decremented by half of the estimated processing time of the task.

- *ReleasedLOR(j):*

  This is defined, for each job type *j*, as the subset of *TotReleasedL* that must be performed on the subset of machines in the facility that a newly released job of type *j* would have to visit.

  This quantity is computed, whenever it is needed to support an order release decision, by summing certain dynamically updated *ReleasedLoadOnMc(i)* values.

At this point, all the quantities necessary to describe different alternative accept/reject and order release rules have been defined and explained, so the next sections present the different alternatives.

3.2.2 Alternative Accept/Reject Rules

Acceptance of an order has a two fold effect on the system. Firstly, there is a possibility that a certain amount of revenue can be earned from the order itself (if it is not tardy by a duration greater than or equal to its critical tardiness). Secondly, its acceptance will cause extra pressure on the existing jobs in the system which might in turn lead to additional tardiness costs for this set of jobs. So philosophically the role of the accept/reject rules can be seen as being to compare the incremental benefit of acceptance of an order against the incremental tardiness costs caused by accepting the order.

In this research, four different alternative accept/reject rules have been defined and implemented. In this section, these rules will be stated together with their possible justification.

(a) Full acceptance (FA)

(b) Accept the order if the total accepted load on the shop is less than a maximum value (TAL)

(c) Accept the order if the load on the busiest machine on the candidate order's route is less than a maximum value (BUS)

(d) Accept or reject the order on the basis of a deterministic simulation to anticipate the effects of these two alternative courses of action (SIMUL).

(a) Full Acceptance (FA)

Definition

All candidate orders are accepted on their arrival to the shop floor.

Discussion

This rule will serve as a benchmark, against which to compare the other rules. When this rule is employed, the manufacturing system is fully exposed to external demand fluctuation.

(b) Total Accepted Load (TAL)

Definition

If the arriving order is a regular order and $TotAcceptedL_t < RegularLimitTotAcceptedL$, the order i in question is accepted, otherwise it is rejected.

If the arriving order is an urgent order and $TotAcceptedL_t < UrgentLimitTotAcceptedL$, the order i in question is accepted, otherwise it is rejected.

Where,

$TotAcceptedL_t$	=	The value of the quantity *TotAcceptedL* (as described before) at the time t of arrival of the order i.
RegularLimitTotAcceptedL	=	A constant
UrgentLimitTotAcceptedL	=	A constant

Discussion

This rule is the simplest of all the rules which allow a job to be rejected and is expected to outperform the FA rule under some conditions. The sole purpose of the rule is to keep the total shop load under control rather than allowing it to grow limitlessly. For an urgent order, the load limit may be larger than that in the case of a regular order in order to attract more revenue (recall that an urgent order yields greater revenue than a regular one of the same estimated total work content). Also, it should be noted that the terms on the left hand side of the acceptance conditions do **not** include the estimated load of the order under consideration for acceptance. This is motivated by the desire to avoid the following bias. If the estimated load of the order is taken into account in the left hand side of the condition, this might cause the larger orders in terms of estimated work content, to be rejected more frequently than the orders with smaller work content.

(c) Accepted Load On The Busiest Machine On the Candidate Order's Route (BUS)

Definition

If the order of type j is a regular one and $AcceptedLoadOnMc(i)_t < RegLimitAcceptedLoadOnMc$, for all $i \subset q_j$, then the order is accepted, otherwise it is rejected.

If the order of type j is an urgent one and $AcceptedLoadOnMc(i)_t < UrgLimitAcceptedLoadOnMc$, for all $i \subset q_j$, then the order is accepted, otherwise it is rejected.

Where,

$AcceptedLoadOnMc(i)_t$	=	The value of the quantity $AcceptedLoadOnMc(i)$ (as described before) for the ith machine at the time t of the arrival of the order.
q_j	=	The set of all machines on the route of an order of type j.
RegLimitAcceptedLoadOnMc	=	A constant.
UrgLimitAcceptedLoadOnMc	=	A constant.

Discussion

This rule is similar to the TAL rule but it is potentially more discerning since it considers more detailed information on the state of the system at the time of the decision. This rule is similar to the one called 'path load order review' as presented in Philipoom and Fry (1992). The authors observe, "Since the machine with the heaviest workload would tend to delay the completion of an order more so than less loaded machines, controlling the input of orders based on this critical machine may make more sense than looking at the entire shop". Here also the absence of the candidate order's individual estimated load in the left hand side of the acceptance conditions arises from the motive of not rejecting the orders with high revenue. As before, each order class has its own acceptance limit so as to allow a preference to the urgent orders if this yields better performance.

(d) Simulation Based Acceptance/Rejection (SIMUL)

Definition

When an order arrives, a pair of pilot deterministic simulation runs are executed to predict the effects of the two decision alternatives. During the first run, the order in question is accepted, while in the second run, the order is rejected. If the profit at the end of the first run exceeds that in the second run by a constant portion, *Kincr*, of the maximum possible profit from the order under consideration, the order is accepted, otherwise, the order is rejected.

Discussion

This rule is conceptually the most sophisticated of the four and has the potential to perform well. This is because this rule uses the full amount of information on the shop floor status including the information on the order itself, the information being generated through pilot simulation runs which consider the detailed evolution of the manufacturing system. In this research, the pilot simulations have been performed deterministically. Also, during the pilot runs, no additional customer orders are considered to arrive, with each run ending when all accepted jobs have been completed.

The success of this rule depends on choosing an appropriate value of the parameter *Kincr*. It can range from zero to unity. When it is zero, it is a too optimistic approach since it means that an order will be accepted whenever the profit from the "accept" run exceeds that from the "reject" run even by small amount. On the other hand, if *Kincr* is unity, it corresponds to a pessimistic situation because in that case the orders are accepted only if they are expected to yield their maximum possible profit. However, neither of these two situations is likely to give the best performance. In the first case (*i.e.* corresponding to *Kincr* = 0), the loss through tardy jobs will be high because the real operation of the manufacturing system consists of uncertain future orders as well as uncertainty in the processing times of the tasks, which are not considered in the pilot runs. In the second case (*i.e.* corresponding to *Kincr* = 1), the loss through rejection of orders will be significantly high. The accepted orders also are not guaranteed to produce a profit (the maximum possible or even less than that) every time owing to uncertain future orders and uncertainty in the task processing time in the real system. So the most suitable value of this parameter *Kincr* will lie in between 0 and 1 which needs to be chosen. The way this choice is done has been detailed in Chapter 5.

3.2.3 Alternative Order Release Rules

As mentioned earlier, in section 3.1.6.2, orders could be released from the Order Release Pool (ORP) at any time and in any quantity. The sequence of the release of orders is also controlled by the order release rule as mentioned below. The basic operation of all order release rules considered in this research is the same and can be described as follows.

The order in the ORP which has the least slack per operation is the first one to be checked for release against the release condition of the active order release rule. In either case, whether this order is released at present or not, another order having the next higher slack per operation is checked for release in the same way as the previous one. In this way all of the orders in the ORP are checked for their possibility of release, whenever checking for order release is initiated.

The time points at which checking is initiated is another issue. Philosophically it might be argued there should be continuous checking, but this is not necessary as almost the same effect can be achieved by checking at some particular points in time. This issue has been addressed in detail in **Appendix E** in the context of describing the logic in the *Phd_OR.mod* file.

If two orders have the same slack per operation and both are eligible to be released, the tie is broken on the basis of the earlier entry time into the system. The tie is broken with certainty as the entry time of each order is unique, owing to the unit batch size of the order arrival process.

There is also a special arrangement to release an order from the ORP forcibly, if it is not released normally by the active order release rule within a certain duration. This duration is individually determined for each order on its arrival to the ORP in the following way. At the moment a new order arrives at the ORP, the average waiting time in any shop queue experienced by a similar order (similar with respect to the class and the number of steps involved) is noted and is multiplied by the number of steps involved in the new order. If this product is less than the flow time allowance of the new order, the said duration is set equal to this product. Otherwise the said duration is set to zero *i.e.* the new order is released from the ORP immediately.

In this research three different order release rules have been defined and implemented. They are:

(a) Immediate release (IMM)

(b) Release the order if the total released load on the shop is less than a defined maximum value (TRL)

(c) Release the order if the released load on the busiest machine on the order's route is less than a maximum value (BUSM).

(a) <u>Immediate Release (IMM)</u>

<u>Definition</u>

An accepted order is released immediately to the shop floor.

<u>Discussion</u>

This rule is considered as the base case in this research.

(b) <u>Total Released Shop Load (TRL)</u>

<u>Definition</u>

If, $TotReleasedL_t < LimitTotReleasedL$, release the order. Otherwise, hold the order in the Order Release Pool (ORP).

Where,

$TotReleasedL_t$	=	The value of the quantity *TotReleasedL* (as described before) at the time of checking the possibility of release.
LimitTotReleasedL	=	A constant.

Discussion

This rule is the simplest of the non-immediate order release rules and is similar in concept to the TAL accept/reject rule in that it bases its decisions solely on the total released shop load. On the left hand side, the estimated work load of the order in question has not been included so as to avoid bias against the release of jobs with higher total work content. Since, in this research, order release is considered very frequently, very little room is created for an order each time an order release is initiated. So if the load of the order is included in the left hand side of the condition of the rule, smaller orders will get always preference over the larger ones for release purposes and the larger orders may be held up in the ORP much longer than the small ones.

The right hand limit is the same for both cases of urgent and regular orders. Differentiation at this point is not necessary because it is intended to make the urgent and regular orders compete on the same basis as the company may lose money through regular orders as well. So a more critical regular order should be released earlier than a less critical urgent order.

(c) Released Load On The Busiest Machine On the Candidate Order's Route (BUSM)

Definition

An order is released from the order release pool if $ReleasedLoadOnMc(i)_t$ < *LimitReleasedLoadOnMc*, for each $i \subset q_j$, otherwise it is held in the order release pool.

Where,

$ReleasedLoadOnMc(i)_t$	=	The value of the quantity $ReleasedLoadOnMc(i)$ (as described before) for the ith machine at the time t.
q_j	=	The set of all machines on the route of the order (of type j) in question.
$i \subset q_j$	=	i is an element of the set q_j.
$LimitReleasedLoadOnMc$	=	A constant.

Discussion

This rule is similar to TRL but potentially more discerning in that it considers more detailed information on the state of the system at the time of the decision. Specifically, it considers the maximum estimated released load on a machine on an order's route at the time of checking the possibility of the order's release. This rule is conceptually more sophisticated than any of the order release rules mentioned so far in this section, since it tries to keep congestion under control by keeping the load of each individual machine below a maximum limit.

The justification for not considering the individual estimated load of the order itself in the left hand side of the condition of the order release rule is as explained in the context of previous rules *i.e.* to avoid bias against "larger" orders. Also, the right hand side limit is the same for both classes of order due to the same reason as stated earlier.

3.2.4 Alternative Dispatching Rules

If there is more than one job in a machine queue then the next job the machine will process when it next becomes idle is selected, in this research, according to one of the dispatching rules listed below:

(a) First-in-System-First-Served (FSFS)

(b) Earliest Due Time (EDT)

(c) Minimum Slack per Operation Remaining (S/OPN)

(a) First-in-System-First-Served (FSFS)

According to this rule, the job which has entered into the system the earliest is selected. No tie is possible since the orders arrive into the system one at a time and hence each order has a unique entry time into the system.

(b) Earliest Due Time (EDT)

According to this dispatching rule, the job which has the earliest due date will be selected. Any tie is broken on the basis of FSFS as stated earlier.

(c) Minimum Slack per Operation (S/OPN)

If all jobs in the queue have positive slack then the job with the minimum slack per remaining operation will be selected. But if there is at least one job with a negative slack then the job, among those with negative slack, which has the maximum (w_i/p_i) will be selected, where w_i is the tardiness cost of the ith job if it is tardy by a unit amount of time and p_i is the estimated imminent processing time of the ith job. Any tie is broken on the basis of FSFS.

3.3 List of Important Parameters Involved

The different parameters involved in the experiments conducted during this research belong to two categories:

(a) Parameters of the manufacturing system which is being controlled

(b) Parameters of the control system.

(a) Parameters of the Manufacturing System

(i) *Demand level:* This parameter dictates the average utilization of the shop, if all arriving orders were accepted. This is actually controlled indirectly by varying a model parameter defining the mean order inter-arrival time given the product mix and routing information. This parameter will be denoted as DL.

(ii) *Demand level variability:* This parameter signifies the uncertainty involved in the demand. This parameter can be varied by changing the coefficient of variation of the distribution of order inter-arrival times. This parameter will be denoted as DLV.

(iii) *Process time variability:* This parameter signifies the uncertainty in the processing times. This can be varied by changing the coefficient of variation of the distribution of the processing times. this parameter will be denoted as PTV.

(iv) *Flow time allowance (regular orders):* While assigning the due time to the regular orders, a constant amount of time is added to the arrival time of the order, which is the externally determined customer lead time for the regular order. This parameter will be denoted as RegFTA

(v) *Flow time allowance (urgent orders):* This parameter signifies the similar quantity as the previous one, but for the urgent orders. This parameter should be set at a lower value than the previous one. This parameter will be denoted as UrgFTA.

(vi) *Proportion of urgent orders:* This is the expected proportion of the orders which are coming into the system, which will be designated as "urgent orders". This parameter will be denoted as PUO.

(vii) *Ku:* This proportionality constant occurs in the calculation of the revenue of an urgent order. Please refer to section 3.1.5.1.

(viii) *Ktr:* This occurs in the tardiness cost calculation of a regular job in the section 3.1.5.2. It is the proportion of the maximum possible revenue that will be lost, if a regular job is tardy by unit time.

(b) Parameters of the control system

All of the control system parameters listed below have been discussed earlier while describing the accept/reject rules or order release rules.

(i) Accept/reject rule options
(ii) Order release rule options
(iii) Dispatching rule options
(iv) RegularLimitTotAcceptedL
(v) UrgentLimitTotAcceptedL
(vi) RegLimitAcceptedLoadOnMc
(vii) UrgLimitAcceptedLoadOnMc
(viii) LimitTotReleasedL
(ix) LimitReleasedLoadOnMc

(x) Kincr.

3.4 Performance Measures of the System

The performance measures used in this research can be grouped into seven categories as shown in the left hand side of **Table 3.1**. within each category a number of different performance measures are involved as shown in the right hand side of the table. Many of the performance measures are computed over all orders and broken down by order class. Where a performance measure is so decomposed, the number of specific variants is shown in the bracket after the measure name. Some of the measures have 15 different variations. These originate when each performance measure is considered on an overall basis (*i.e.* considering all orders irrespective of category or number of steps), on the basis of the category of order (*i.e.* considering the order as urgent or as regular, thus producing two more variants), on the basis of the number of steps involved in an order (*i.e.* whether the order is a 1, 2, 3, or a 4-step order and thus giving rise to another four variants) and lastly on the basis of combination of category and number of steps involved in an order (which produces eight more variants of the same performance measure). Also there are several performance measures which have 10 variants each. These ten variants originate from considering the ten machines in the manufacturing system.

Among the above performance measures the first three measures under category (A) need to be defined for clarity.

The 15 variants of "Percent achievement" (PA) are:

Overall Percent Achievement (OPA),
Urgent Percent Achievement (UPA),

Table 3.1: Performance Measures

Category		Family of Performance Measures
(A)	Cost related measures:	Percent achievement (15) Percent rejection loss (15) Percent tardy loss (15)
(B)	Delivery related measures:	Tardiness (15) Lateness (15) Earliness (15) Percent tardy (15)
(C)	Rejection related measures:	Percent rejected (15)
(D)	Flow time related measures:	Flow time (15) Manufacturing lead time (15) Variability in flow time (15)
(E)	Queue related measures:	Waiting time in a queue (15) Waiting time in the order release pool (15) Waiting time in machine queues (15) Order release queue length (in number) (1) Order release queue length (in load) (1) Waiting time in a specific machine queue (10) Specific machine queue length (in number) (10) Specific machine queue length (in load) (10) Variability in load in specific machine queue (10)
(F)	Work in process related measures:	Work in process (in number) (15) Work in process (in load) (15) Accepted load on specific machine (10) Released load on specific machine (10)
(G)	Utilization related measures:	Specific machine utilization (10) Average machine utilization (1)

Regular Percent Achievement (RPA),

x-step Percent Achievement (xPA), for $x = 1, 2, 3$, or 4,

Urgent x-step Percent Achievement (UxPA), for $x = 1, 2, 3$, or 4, and

Regular x-step Percent Achievement (RxPA), for $x = 1, 2, 3$, or 4.

The 15 variants of "Percent rejection loss" (PRL) are:

Overall Percent Rejection Loss (OPRL),
Urgent Percent Rejection Loss (UPRL),
Regular Percent Rejection Loss (RPRL),
x-step Percent Rejection Loss (xPRL), for $x = 1, 2, 3$, or 4,
Urgent x-step Percent Rejection Loss (UxPRL), for $x = 1, 2, 3$, or 4, and
Regular x-step Percent Rejection Loss (RxPRL), for $x = 1, 2, 3$, or 4.

The 15 variants of "Percent tardy loss" (PTL) are:

Overall Percent Tardy Loss (OPTL),
Urgent Percent Tardy Loss (UPTL),
Regular Percent Tardy Loss (RPTL),
x-step Percent Tardy Loss (xPTL), for $x = 1, 2, 3$, or 4,
Urgent x-step Percent Tardy Loss (UxPTL), for $x = 1, 2, 3$, or 4, and
Regular x-step Percent Tardy Loss (RxPTL), for $x = 1, 2, 3$, or 4.

The three different types of measure defined above are based on the specific orders arriving during a period of time as follows:

zPA = $100 \times$ (Actually earned revenue by orders of kind z / Maximum possible revenue that could have been earned by the orders of kind z),

zPRL = $100 \times$ (Loss through rejected orders of kind z / Maximum possible revenue that could have been earned by the orders of kind z), and

zPTL = $100 \times$ (Loss through tardy orders of kind z / Maximum possible revenue that could have been earned by the orders of kind z),

where, z is a string from {"O", "U", "R", "x", "Ux", or "Rx", for $x = 1, 2, 3$, or 4}. From the above definition of zPA, for instance, the definition of U3PA can be obtained by substituting "U3" in the place of z. Clearly for any valid z, zPA + zPRL + zPTL = 100.

Now, the orders of kind "O" means the orders of any kind irrespective of any category or number of steps. The orders of kind "U" and "R" represent the urgent and regular orders respectively, and lastly, the orders of "Ux" and "Rx" represent the urgent x-step and regular x-step orders respectively, where x can have a value from 1, 2, 3, or 4.

So for example, using the above definitions,

UPRL = 100 × (Loss through rejected urgent orders / Maximum possible revenue that could have been earned by the urgent orders)

The rest of the performance measures in **Table 3.1** are hopefully self-explanatory.

In this research the key performance measure is Overall Percent Achievement (OPA) which gives the actual performance of the system as a percentage of the best possible performance. I.e. for a given demand level, maximizing OPA is equivalent to maximizing profit (considering both rejection and tardiness cost). The best possible performance corresponds to the situation when all orders are accepted and completed on time. However the actual performance will be less than this maximum value in many situations due to the rejection of some of the candidate orders and/or due to the tardiness of some of the accepted orders. An order, if accepted and completed on time, contributes to the earnings of the company by a certain amount, which is equal to Rev_i (see section 3.1.5.1). If an order is rejected however, the resulting loss is equal to its contribution, assuming it were accepted and completed on time but there will not be any additional penalty imposed due to this rejection.

3.5 List of Assumptions in the Hypothetical System

(a) The shop layout, in terms of the number of machines and their organization into work centres, is as described earlier.

(b) The batch size of the arrival process is unity and an arrival can occur at any time.

(c) Orders are coming directly from the customers and the accepted orders are manufactured and shipped to the customer directly.

(d) The product mix as well as the process plan of a particular job type is fixed and known beforehand.

(e) The process time as indicated in the process plan includes set up time.

(f) Any number of orders can be released from the order release pool at any time if so permitted by the active OR rule.

(g) If a job is being processed by a machine, it cannot be preempted by any other job.

(h) A machine can process one job at a time.

(i) A machine does not need to wait for any operator to start processing, *i.e.* if a job finds a machine idle for which it was waiting, the job can be started processing without any delay.

(j) There is no rework necessary at any machine.

(k) The time to transfer from one point to another is zero.

(l) There is infinite buffer space for any machine.

(m) There is no downtime or maintenance for the machines.

(n) The manufacturing system operates continuously.

(o) A job can be processed by one machine at a time.

3.6 Description of the SIMAN Simulation Model

The hypothetical system that has been described in detail so far has been translated into a computer simulation model using SIMAN. This section describes the organization of different components of the model as shown in **Table 3.2**. A description of the code and the main features of the model can be found in **Appendix E**.

The logic of the simulation model resides mainly in four different files. They are: (i) *Phd.mod* (ii) *Phd_AR.mod* (iii) *Phd_OR.mod*, and (iv) *Phd_DR.mod*. The latter three files deal with the logic segments regarding accept/reject rules, order release rules and dispatching rules respectively, while the first file contains the main body of the logic. *Phd.exp* is the experiment file where the declarations of all necessary attributes, variables, queues, resources, stations, files *etc.* are located together with other statistics collection elements. There is another file called *JobInfoFile*, which carries all the information regarding the process plans of different types of order. This file serves as an input file to the simulation program.

Table 3.2: Organization of Different Parts of the Model

<table>
<tr><td rowspan="5">Source Code
(Before compilation)</td><td>Function of the model segments</td><td>Model Listing Segments</td><td>Experiment Listing</td><td>C User Code
(In case of simulation based accept/reject rule only)</td></tr>
<tr><td>Accept/Reject</td><td>Phd_AR.mod</td><td rowspan="4">Phd.exp</td><td rowspan="4">Phdc.c</td></tr>
<tr><td>Order Release</td><td>Phd_OR.mod</td></tr>
<tr><td>Dispatching</td><td>Phd_DR.mod</td></tr>
<tr><td>Rest of the logic</td><td>Phd.mod</td></tr>
<tr><td colspan="2">Output Files
(After Compilation)</td><td>Phd.m</td><td>Phd.e</td><td rowspan="2">Phdc
(after compiling and linking the source user code Phdc.c with SIMAN libraries)</td></tr>
<tr><td colspan="2">Program Files
(After Linking)</td><td colspan="2">Phd.p</td></tr>
<tr><td colspan="2">Executable (which uses Phd.p as the argument)</td><td colspan="2">siman
(for non-simulation based accept/reject rules)</td><td>Phdc
(for the simulation-based accept/reject rule)</td></tr>
</table>

If a control policy with the simulation based accept/reject rule is used, it is necessary to make use of one additional file containing code which is in the file *Phdc.c*, written in C. Otherwise, the above files are sufficient to run any control policy, which is a combination of a non-simulation based accept/reject rule, an order release rule and a dispatching rule.

In order for a simulation run to be made, which enables the performance of a particular set of control parameters under a particular set of manufacturing system parameters to be predicted, it is necessary to specify a value for each of the parameters defined earlier in section 3.3. The next two chapters will report on a wide range of simulations which have been conducted during this research.

Chapter 4

Preliminary Experiments and Analysis

The purpose of this chapter is to present the results of various exploratory experiments which have been carried out on the system described in the previous chapter. The chapter begins by identifying and defining the experimental factors. Next a set of exploratory studies follow intended to develop a preliminary understanding of how the basic system works when all orders are accepted and all accepted orders are released to the shop floor immediately. After this, a relatively more complex study is presented which investigates how the system performs under different combinations of accept/reject rules, order release rules and dispatching rules.

Both this and the subsequent chapter make extensive use of acronyms to refer to both experimental factors and performance measures. To aid the reader, a detailed glossary containing all of these acronyms is provided in **Appendix D**.

4.1 Chosen Parameters

The following list summarizes the experimental factors which can be easily varied for the system under study:

(a) Demand level (DL),

(b) Demand level variability (DLV),

(c) Process time variability (PTV),

(d) Proportion of urgent orders (PUO),

(e) Due date tightness (DDT),

(f) Accept/reject rule options (AR),

(g) Order release rule options (OR),

(h) Dispatching rule options (DR),

(i) RegularLimitTotAcceptedL (RL_TAL),

(j) UrgentLimitTotAcceptedL (HL_TAL)[1],

(k) RegLimitAcceptedLoadOnMc (RL_BUS),

(l) UrgLimitAcceptedLoadOnMc (HL_BUS),

(m) LimitTotReleasedL (CL_TRL),

(n) LimitReleasedLoadOnMc (CL_BUSM),

(o) Kincr.

Each of the parameters from (i) to (l) in the above list is involved in one of the accept/reject rules mentioned earlier. In a context when there is no ambiguity about which accept/reject rule is being used, the associated control limits *i.e.* the parameters (i) through (l) will be referred to by simply RL (instead of RL_TAL or RL_BUS) and HL (instead of HL_TAL and HL_BUS) as appropriate. Each of the parameters (m) and (n) in the list is involved in one of the order release rule options. Similarly when the context is clear about which order release rule is being used, the corresponding control limit will be referred to by CL only (instead of CL_TRL or CL_BUSM).

In the previous chapter, all of these factors except DDT have been clearly defined. In the

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[1] Note that since urgent orders in a manufacturing setting are commonly referred to as "hot", parameters relevant to this class of orders have been named using the letter 'H' (for "hot") instead of 'U' (for "urgent").

following section. DDT is discussed in general and also how it is precisely defined in this research.

4.1.1 Due Date Tightness

Gordon (1995) described due date tightness (DDT) as "Average due date tightness is one possible measure of the severity of response requirements of the system." DDT can be specified in various ways as the examples provided by Cheng and Chen (1997) demonstrate via describing eight different due date assignment rules. In each of these rules, as explained below, the value of *k* is related to the level of DDT with DDT increasing as *k* decreases in all cases.

Constant Flow:	$d_i = r_i + k$
Equal Slack:	$d_i = r_i + P_i + k$
Number of Operations:	$d_i = r_i + kN_i$
Total Work:	$d_i = r_i + kP_i$
Processing Plus Waiting:	$d_i = r_i + P_i + kN_i$
Jobs In System:	$d_i = r_i + kJIS_i$
Jobs In Queue:	$d_i = r_i + kJIQ_i$
Work In Queue:	$d_i = r_i + kWIQ_i$

where,

where,	d_i	=	Due time of the *i*th order,
	r_i	=	Arrival time of the *i*th order.
	P_i	=	Total processing time of the *i*th order,
	N_i	=	Number of operations of the *i*th order,
	JIS_i	=	Number of jobs in the system. when the *i*th order arrives,
	JIQ_i	=	Number of jobs in the work center queues on the *i*th order's routing when it arrives,

WIQ_i = Total work in the work center queues on the ith job's routing when it arrives.

The importance of due date tightness lies in the fact that the selection of the level of this quantity significantly affects the due date performance of the orders. When due dates can be influenced, an implicit objective is to assign due dates as tight as possible. Although loose comfortable due dates reduce the mean tardiness and the percent of tardy orders, tight due dates, provided that a manufacturer is able to meet them, attract more customers in a competitive market and imply better customer service.

What should be considered as the measure of due date tightness really depends upon the principal performance measure of the system at hand. For example in most of the existing studies the due date tightness has been expressed as a function of flow allowance, and some combination of job attributes and the current status of the shop floor.

In these studies cost information was usually not considered. What should be the measure of due date tightness when some kind of cost information is involved (as in the present system for which the different kinds of cost component involved have been already mentioned in the previous chapter), is not straightforward.

In the present system the principal performance measure is *Overall Percent Achievement (OPA)*, which was defined in section 3.4 and which can also be expressed as:

$$\mathrm{OPA} = 100 \times \left[1 - \frac{\text{Total loss from all orders}}{\text{Maximum possible revenue that could have been earned from all orders}} \right]$$

The severity of the pressure of meeting due date requirements in a particular situation given this objective depends on many parameters of the system. Among them demand level, flow time allowance, tardiness cost factor are the three most significant parameters which affect and determine how difficult it might be to achieve a high OPA.

As can be seen from equations (3.4a) and (3.4b), the tardiness loss depends on Ktr and RegFTA in the case of a regular order and by Ktu and UrgFTA in the case of an urgent order.

If the flow time allowance (RegFTA or UrgFTA) increases, the tardiness of an already tardy order decreases and hence OPA increases. Again if Ktr (and hence Ktu, as they are related) decreases, tardiness loss decreases and hence OPA increases.

So from the above analysis it is clear that RegFTA, UrgFTA, Ktr, Ktu are the fundamental parameters in addition to demand level (DL) which primarily control OPA *i.e.* these parameters control how difficult or how easy is the situation with respect to improving the performance measure of the system. To specify a level of due date tightness, it is needed to specify the set {DL, RegFTA, UrgFTA, Ktr, Ktu} when other factors (*e.g.* DLV, PTV) are kept at certain values.

If the system encounters a situation with higher DL, shorter flow allowance, higher Ktr (and hence higher Ktu) or any combination of them then the situation will correspond to a tighter level of DDT, compared to the loose level of DDT, where DL is lower, flow allowance is larger and Ktr is smaller or any combination of these three. In the present research DL is already considered as a separate experimental factor on its own, so DL has been decoupled from the definition of DDT and only a set of values of flow allowance and tardiness cost factor is considered to define a level of DDT. In the experiments in this thesis, the due date tightness has been varied at two such different levels, which will be mentioned in the next section.

4.2 The Choice of Different Factor Levels for the Preliminary Experiments

Immediately below are listed the factor levels of the main experimental factors, which are used in the preliminary study. In later text these five factors are often referred to as the "environmental factors" since in a real manufacturing environment they would be beyond an organization's control.

DL	=	{0.75, 0.80, **0.85**, 0.90, 0.95}
DLV	=	{**0.1**, 0.35, 0.6, 0.85, 1.0}
PTV	=	{**0.1**, 0.2, 0.3}
PUO	=	{0, **0.05**, 0.10, 0.15, 0.20}
DDT	=	{"**Loose**", "Tight"}

The base levels of the above five parameters are {0.85, 0.1, 0.1, 0.05, "Loose"} in order of their appearance.

A "Loose" level of DDT is characterized by the values of RegFTA = 30, UrgFTA = 20, and Ktr = 0.03333 with these values chosen so that they yield OPA = 90% (approximately) when working with AR = FA, OR = IMM, and DR = FSFS under an environment such that all of the environmental factors are at their base levels. Note that these settings imply that an order will lose all its revenue if it is tardy by its flow allowance.

A "Tight" level of DDT is set with RegFTA = 21, UrgFTA = 14, and Ktr = 0.05952 so that the system can achieve OPA = 58% (approximately) when working under the same conditions as in the case of the "Loose" level. Note that with these settings, if a regular order or an urgent order is tardy by 80% of its flow time allowance, the order will lose all its revenue.

To understand the significance of the levels chosen for the variability in the arrival process, the probability density functions (of the underlying Gamma distribution) for the inter-arrival time have been plotted in **Figure 4.1** with the coefficient of variation equal to the values in the set {0.1, 0.35, 1.0} and with the mean value in all three cases being 1.0.

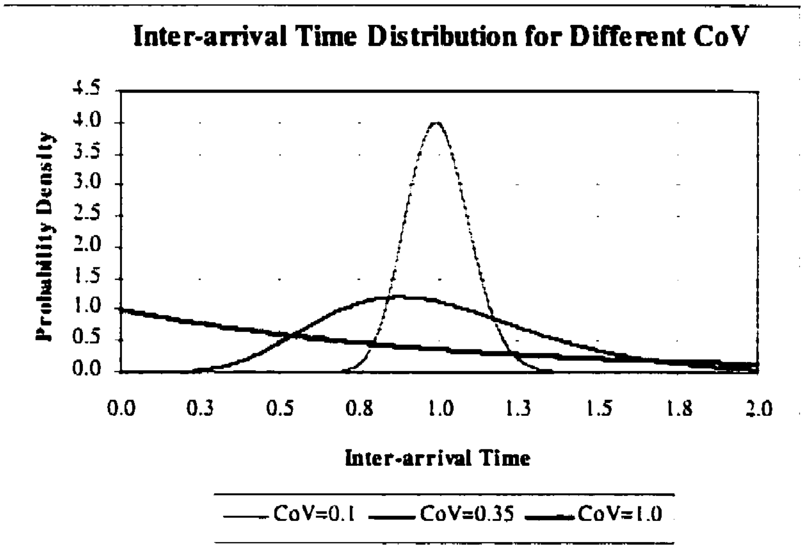

Figure 4.1: Gamma Distribution at Different CoV

The Kr and Ku parameters are not varied during the experiments. Kr has been arbitrarily chosen as unity while Ku has been set equal to 1.25, *i.e.* each urgent order will have 25% more potential revenue than a regular order of same job type.

4.3 Preliminary Studies on the System Under Full Acceptance

This section reports on a series of experiments which are exploratory in nature, their purpose being to explore how the basic system performs *without* implementing any input control strategy as the environmental factors are varied. The specific preliminary studies that have been carried out are the following:

(a) When only regular orders are involved, and all arriving orders are accepted and released to the shop floor immediately and the active dispatching rule is FSFS,

(i) How do OPA and RxPA (for x = 1,2,3 or, 4) vary with respect to DL, DLV, PTV, RegFTA and Ktr?

(ii) How does overall flow time (OFT) and the flow time for x-step orders (RxFT), where x = 1,2,3 or, 4 vary with respect to DL, DLV, PTV?

(b) When there are two categories of order (one being relatively more urgent than the other) and when all arriving orders are accepted and released to the shop floor immediately and the active dispatching rule is S/OPN,

(i) How do OPA, RxPA and UxPA (for x = 1,2,3 or, 4) vary with respect to DL, DLV, PTV, RegFTA, UrgFTA, and Ktr?

(ii) How does overall flow time (OFT) and the flow time for x-step orders (RxFT, UxFT), where x = 1,2,3 or, 4 vary with respect to DL, DLV, PTV, RegFTA, and UrgFTA?

In the first set of experiments only regular orders were considered and the dispatching rule used was FSFS, while in the second set, urgent orders were also considered and the dispatching rule used was S/OPN. In all experiments the system was simulated for 5 replications each of length 83520 hours after a warm-up period of 11520 hours. From the first replication of each experiment in the first set, a sufficient number of values of different quantities were written to an external file and were subsequently processed by a spreadsheet to be used in the study of the scenarios where only regular orders are involved.

4.3.1 Findings from the Preliminary Studies

4.3.1.1 <u>All Regular Orders</u>

(i) **Table 4.1** shows the calculated values of different variants of percent achievements (*i.e.* OPA and RxPA) as obtained from the spreadsheet at a fixed value of Ktr =

0.05567, for different values of DL and RegFTA as shown. Here, each of DLV and PTV was fixed at 0.1.

Table 4.1: OPA and RxPA at Different Values of DL and RegFTA (fixed Ktr)

	DL = 0.75			DL = 0.85			DL = 0.95		
RegFT	10	16	22	10	16	22	10	16	22
OPA	94.33	97.11	98.86	88.30	91.53	94.29	46.76	50.41	53.94
R1PA	95.97	98.32	99.45	88.60	92.52	95.37	23.68	30.32	36.30
R2PA	94.52	97.46	99.06	87.34	91.28	94.41	35.59	40.80	45.62
R3PA	94.31	97.12	98.82	88.39	91.62	94.34	48.25	51.71	55.13
R4PA	94.13	96.82	98.75	88.71	91.48	94.04	52.84	55.62	58.40

From the table it is clear that for the same value of DL, if RegFTA is increased each of the performance measures is going to improve. Also, for the same RegFTA if DL is increased, performance is going to worsen.

From the simulation of the system, the values of OPA and RxPA for different values of DLV and PTV are shown in **Figure 4.2** and **Figure 4.3**, when DL was at 0.75 and other environmental factors are held fixed at their base levels. It can be observed from **Figure 4.2** that, as DLV increases, OPA and RxPA (for x = 1, 2, 3, 4) decrease. Also, for larger x, RxPA is affected more and its value decreases at a faster rate, with the increase of DLV. Similar observation can be made from **Figure 4.3** which shows that as PTV increases OPA and RxPA decrease.

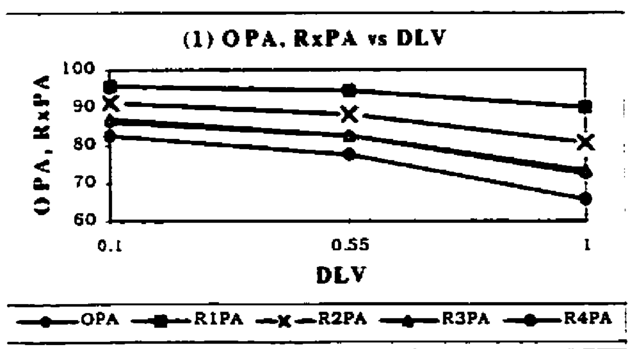

Figure 4.2: Effect of DLV on OPA and RxPA

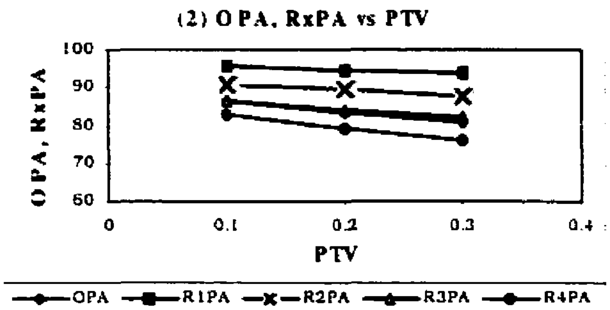

Figure 4.3: Effect of PTV on OPA and RxPA

(ii) To explore how flow time is affected with respect to DL, DLV and PTV, both the mean and the coefficient of variation (CoV) of flow time were observed. When DL was being varied, DLV and PTV were kept at 0.1 and when either of DLV or PTV was varied, DL was held at a value of 0.75. The results are shown in **Table 4.2**. From the table it can be seen that both the mean and the coefficient of variation of any variant of flow time (*i.e.* OFT and RxFT) increase with the increase of DL, DLV or PTV.

Table 4.2: Mean and CoV of OFT, RxFT for Different DL, DLV and PTV

		DL			DLV			PTV	
		0.75	**0.85**	**0.95**	**0.10**	**0.55**	**1.00**	**0.10**	**0.30**
Mean	OFT	18.07	27.60	97.24	18.07	18.92	20.99	18.07	19.23
	R1FT	8.68	14.31	52.82	8.68	9.20	10.40	8.68	9.16
	R2FT	14.87	23.44	83.29	14.87	15.60	17.46	14.87	15.81
	R3FT	19.12	29.15	102.49	19.12	20.01	22.20	19.12	20.32
	R4FT	22.23	33.02	115.22	22.23	23.23	25.55	22.23	23.73
CoV	OFT	0.43	0.48	0.69	0.43	0.45	0.49	0.43	0.46
	R1FT	0.83	0.89	1.09	0.83	0.86	0.90	0.83	0.87
	R2FT	0.50	0.56	0.78	0.50	0.53	0.57	0.50	0.53
	R3FT	0.36	0.42	0.65	0.36	0.39	0.43	0.36	0.39
	R4FT	0.27	0.34	0.58	0.27	0.30	0.35	0.27	0.30

Also it is interesting to observe at this point how the potential revenue (*i.e.* the maximum possible revenue that can be earned if all orders are accepted and finished on time), tardiness cost, and actual revenue earned (*i.e.* potential revenue less tardiness cost) vary as the demand level increases in the situation when all orders are regular and are accepted and released to the shop floor immediately, when all the environmental factors are at their base levels. This is shown in **Figure 4.4**.

This has also been compared with the situation when all orders are regular and the orders are accepted according to the BUS AR rule with a fixed value of RL_BUS (= 29.05 hours), and the accepted orders are released to the shop floor immediately, when all the environmental factors are kept at their base levels. This latter case is depicted in **Figure 4.5**.

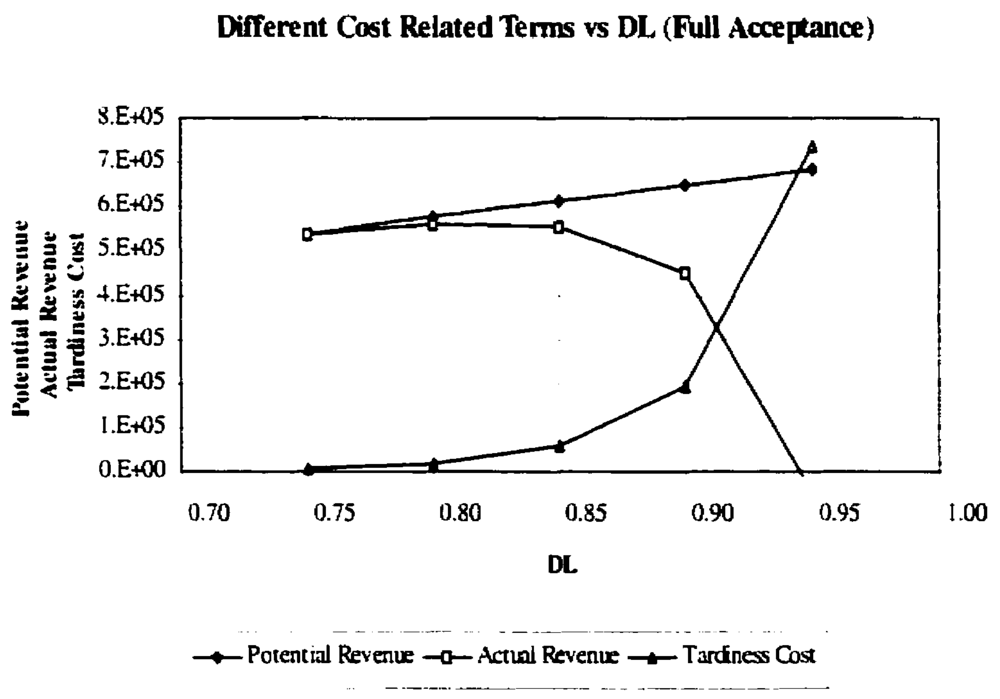

Figure 4.4: Different Cost Related Terms vs DL (Full Acceptance)

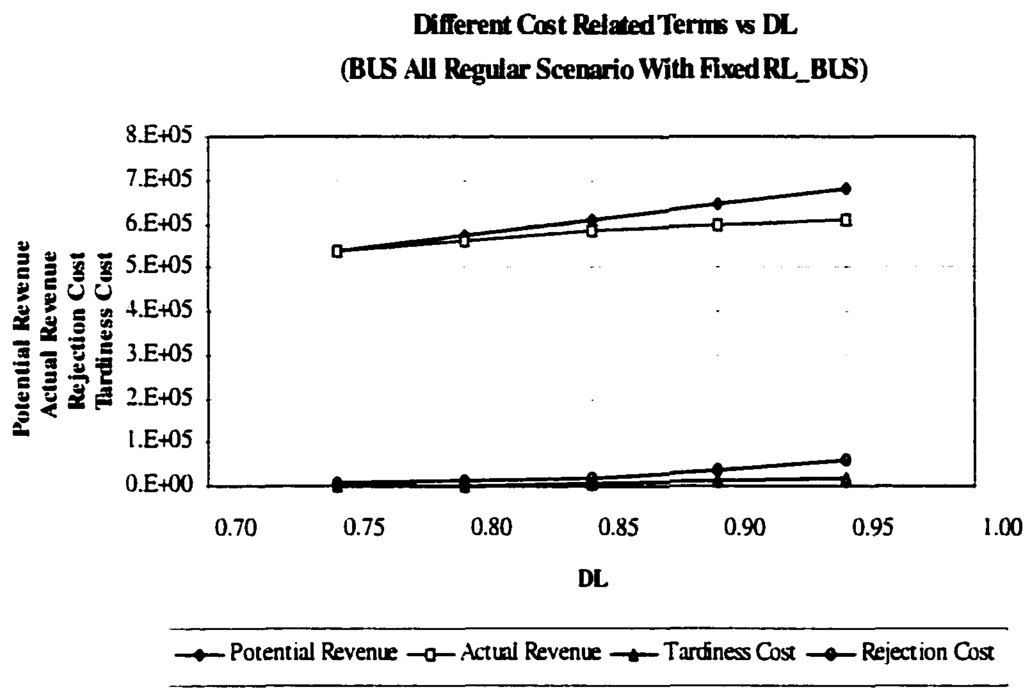

Figure 4.5: Different Cost Related Terms vs DL (BUS All Regular Scenario With Fixed RL_BUS)

4.3.1.2 <u>Two Classes of Order</u>

(i) To study how OPA, RxPA and UxPA (for x = 1, 2, 3, 4) vary with respect to DL, DLV, PTV, RegFTA and UrgFTA in the two order class scenario, each of these factors was varied on its own across the values listed below, while other factors were kept at the values shown in bold font in the following list.

DL	=	{0.75, **0.85**, 0.95}
DLV	=	{**0.1**, 0.55, 1.0}
PTV	=	{**0.1**, 0.3}
PUO	=	{**0.05**, 0.15, 0.25}
RegFTA	=	{25, **30**, 35}
UrgFTA	=	{10, 15, **20**}

The full results from these experiments are tabulated in **Appendix F**. The results show that OPA or any variant of OPA (*i.e.* RxPA or UxPA), is affected by DL, DLV and PTV in a similar way as in the case of all regular orders. With increasing DL, DLV or PTV, OPA or any of its variants decreases. In addition to this effect, what is interesting is the effect of RegFTA, UrgFTA and PUO on OPA, RxPA and UxPA. The corresponding results from the Appendix F are reproduced in the following **Table 4.3** for easy reference.

Table 4.3: OPA, RxPA and UxPA for Different PUO, RegFTA and UrgFTA

	PUO			**RegFTA**			**UrgFTA**		
	0.05	**0.15**	**0.25**	**25**	**30**	**35**	**10**	**15**	**20**
OPA	90.18	88.56	86.81	84.03	90.18	94.14	87.26	89.05	90.18
RPA	89.92	87.53	84.63	83.56	89.92	94.01	89.01	89.02	89.92
UPA	94.20	93.29	92.06	91.19	94.20	96.13	60.65	89.45	94.20
R1PA	76.08	71.73	66.89	58.45	76.08	85.83	72.81	73.38	76.08
R2PA	78.71	73.91	68.97	64.89	78.71	87.48	76.59	76.33	78.71
R3PA	91.38	89.17	86.24	86.18	91.38	94.88	90.76	90.88	91.38
R4PA	95.07	93.83	92.19	92.05	95.07	96.97	94.60	94.59	95.07
U1PA	82.83	82.06	76.14	54.12	82.83	92.18	96.13	89.95	82.83
U2PA	94.89	93.91	92.60	88.27	94.89	97.37	89.64	94.77	94.89
U3PA	95.32	94.18	93.12	93.91	95.32	96.72	68.52	91.93	95.32
U4PA	93.23	92.63	91.55	92.03	93.23	94.99	32.07	83.31	93.23

If PUO increases, each of OPA, RPA, UPA, RxPA, and UxPA (for x = 1, 2, 3, 4) decreases. This is due to the fact that as PUO increases the average job flow allowance decreases which leads to an increase in tardiness costs.

When RegFTA increases, OPA and RPA increase because the regular orders in the system will have more flow allowance and hence the tardiness of the already tardy orders will decrease. Interestingly UPA also improves since under a S/OPN dispatching rule, increasing RegFTA will cause urgent orders to be even more high priority than usual.

For a similar reason, when UrgFTA increases, all of the percent achievement values increase irrespective of order class.

(ii) Using the same settings as in (i), the influence of DL, DLV, PTV, PUO, RegFTA and UrgFTA on overall flow time and its different variants has been studied. In each case, both the mean and the coefficient of variation was observed. The important observations from the results are as follows. If DL, DLV or PTV increases, both the mean and the coefficient of variation of any kind of flow time increases. If PUO is increased, the mean and the coefficient of variation of the flow time again increases. As the flow allowance of one class of order increases, the mean of any variant of its flow time rises, while that of the other class of orders goes down. This also can be attributed to S/OPN being the active DR here, as explained earlier. A complete tabulation of results is given in Appendix F.

4.4 Preliminary Experiments Involving Input Control Mechanisms

This section reports on two sets of experiments which involve a two stage input control mechanism *i.e.* a situation where the system is working under the control of an accept/reject rule and an order release rule. In the first set of experiments, no urgent orders are considered and the objective is to observe, analyze and understand the behavior of the two stage input control mechanism when the control limits involved in the accept/reject rule and the order release rule are varied. The setup of this set of experiments is described in detail in the next section. The second set of experiments mainly deal with different combinations of accept/reject rule, order release rule and dispatch rule, when two classes of orders are considered. The focus of this second set of experiments is on examining the impact on OPA of different combinations of levels of the control limits that are involved in the accept/reject rules and order release rules.

4.4.1 Experiments Involving Only "Regular" Orders

Immediately below are listed the values of the environmental factors and the main qualitative control parameters used in these experiments:

DL	=	85%	DDT	=	Loose
DLV	=	0.1	AR	=	BUS
PTV	=	0.1	OR	=	BUSM
PUO	=	0%	DR	=	FSFS

The environmental factors (except PUO) have been kept at their base levels. In these experiments RL_BUS has been varied through {10, 15, 20, 25, 30, 35} hours and for each value of RL_BUS, CL_BUSM has been varied through {5, 10, 15, 20, 25, 30, 35} hours. In carrying out each experiment, the system has been simulated for 5 replications, during each of which statistics were collected for 72000 hours after a warm-up period of 11520 hours so that the half-widths of the estimated performance measures of interest are within 0.1% of their mean values.

The performance measures that have been observed in these experiments are as follows:

- OPA, OPTL, OPRL,
- Overall flow time (OFT), Overall manufacturing lead time (OMLT), Overall waiting time in the order release pool (OWTORP),
- Variability (*i.e.* CoV) in the load in the order release pool, and
- Variability (*i.e.* CoV) in OFT.

The objective of this set of experiments was to explore how varying the control limits of the AR and OR rules effects a number of important performance measures including OPA, OPTL, OPRL, OFT, OMLT, OWTORP, and also the variability of OFT as well as that of the load in the ORP in the presence of an AR rule other than full acceptance.

4.4.1.1 Effect on OPA, OPTL and OPRL

The values of OPA, OPTL and OPRL from the experiments have been plotted and presented in **Figure 4.6**. Each point in a plot represents the average of the five averages of the corresponding quantity from the five simulation replications. Each plot is drawn at a particular level of RL_BUS, when CL_BUSM is being varied.

The following observations can be made from this experiment:

(a) At any level of RL_BUS, OPA increases with CL_BUSM,

(b) At a particular RL_BUS, OPTL decreases with increasing CL_BUSM,

(c) At a particular RL_BUS, OPRL decreases with the increase of CL_BUSM,

(d) There is an optimum value of RL_BUS for which the system achieves the maximum possible OPA,

(e) At a particular CL_BUSM, OPTL decreases with RL_BUS,

(f) At a particular CL_BUSM, OPRL increases with the decrease of RL_BUS.

At a fixed level of RL_BUS, a lower value of CL_BUSM causes the system on average to hold an order in the order release queue for a longer time. Due to this the average overall manufacturing lead time (OMLT) will reduce (as will be seen in the next section) but this yields no improvement in overall flow time due to the increase in the average overall waiting time in the order release queue (OWTORQ). As a result OPTL increases as CL_BUSM decreases. Also as the average speed of jobs through the system decreases, overall congestion in the system increases, which results in OPRL also increasing as CL_BUSM decreases. Thus, the system suffers larger losses as CL_BUSM decreases or, in other words, OPA increases with CL_BUSM. What the value of OPA at a particular combination of RL_BUS and CL_BUSM will be, depends on how much loss (through tardiness and rejection loss) is caused. It has been already seen that at a particular value of RL_BUS, OPA depends on CL_BUSM. Now at a fixed CL_BUSM, if RL_BUS increases the system will accept more

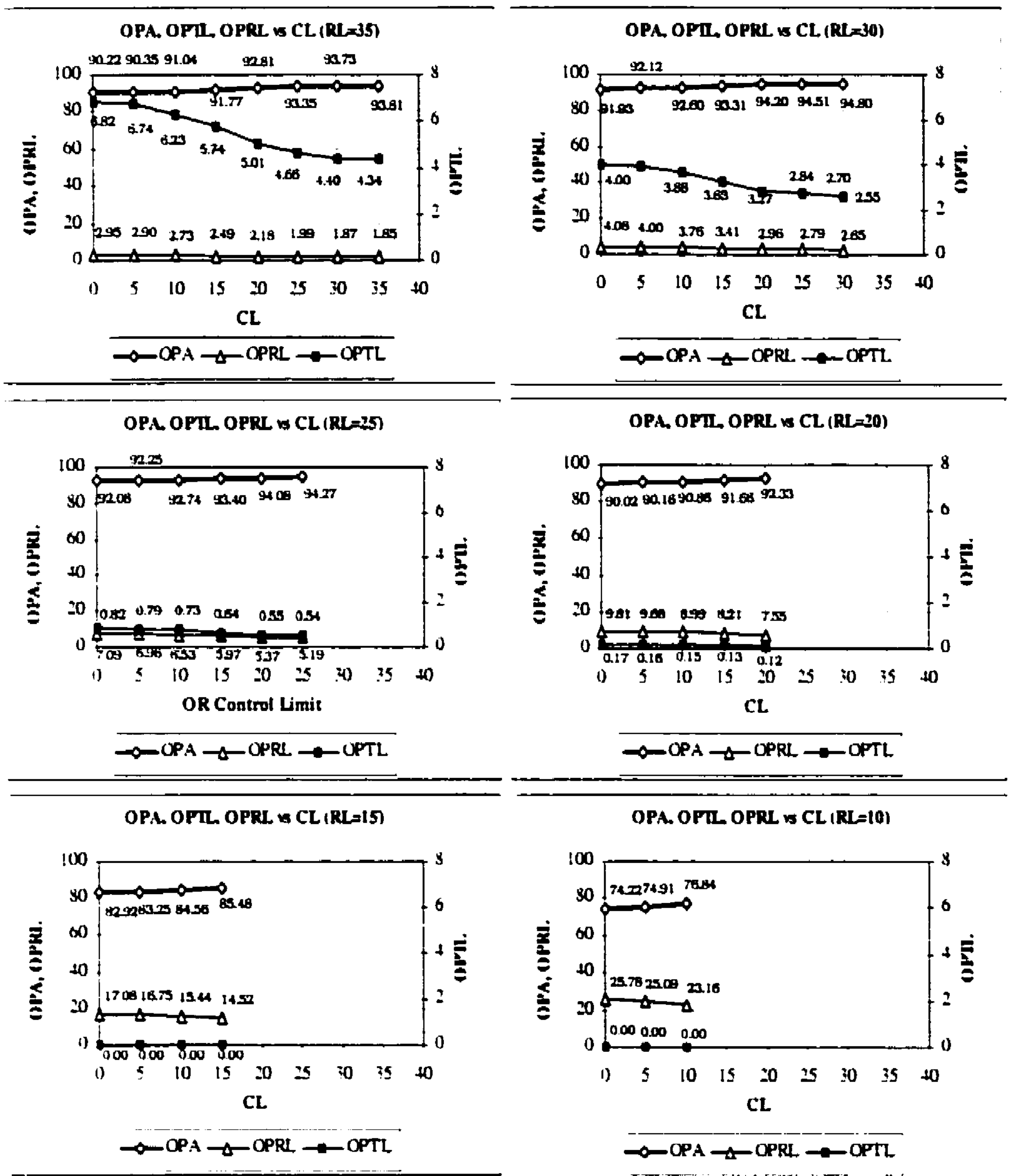

Figure 4.6: OPA, OPTL, OPRL vs. CL (for Different Values of RL)

orders and this will make OPTL increase owing to the increased load in the order release queue, although it will reduce OPRL. So the maximum OPA will correspond to that set of values of the control limits which makes the total loss minimum. As at a particular RL_BUS, OPA increases with CL_BUSM until average OWTORQ becomes zero, so it can be said that for this manufacturing system, under these specific conditions, immediate release of the accepted orders to the shop floor will give the best OPA. So the remaining control limits that need to be properly chosen are the control limits of the active accept/reject rule (*i.e.* CL_BUSM can be set to equal RL_BUS to cause immediate release of accepted orders).

4.4.1.2 Effect on OFT, OMLT and OWTORQ

Figure 4.7 presents the effects on OFT. OMLT and OWTORQ. Plots have been drawn in the same manner as for the previous set of plots.

The following observations can be made from this experiment:

(a) At any particular RL_BUS, with the decrease of CL_BUSM, OFT increases, OMLT decreases and OWTORQ increases at a higher rate than OMLT decreases,

(b) At a particular CL_BUSM, if RL_BUS decreases, OFT, OMLT and OWTORQ decrease.

At a particular RL_BUS if CL_BUSM decreases, an accepted order, on average, will be held up in the order release queue for a longer time which causes the shop floor to be less congested and OMLT to decrease. However as the increase in OWTORQ is larger than the decrease in OMLT, OFT (being the sum of those two), consequently increases. If RL_BUS decreases, the system rejects more orders and hence it will be less congested which will result in decreased OMLT. Also, the order release queue will not be overloaded and due to less jobs in the system, orders from the order release queue are released quickly which results in decreased OWTORQ. Since both OMLT and OWTORQ decrease, clearly OFT will decrease too.

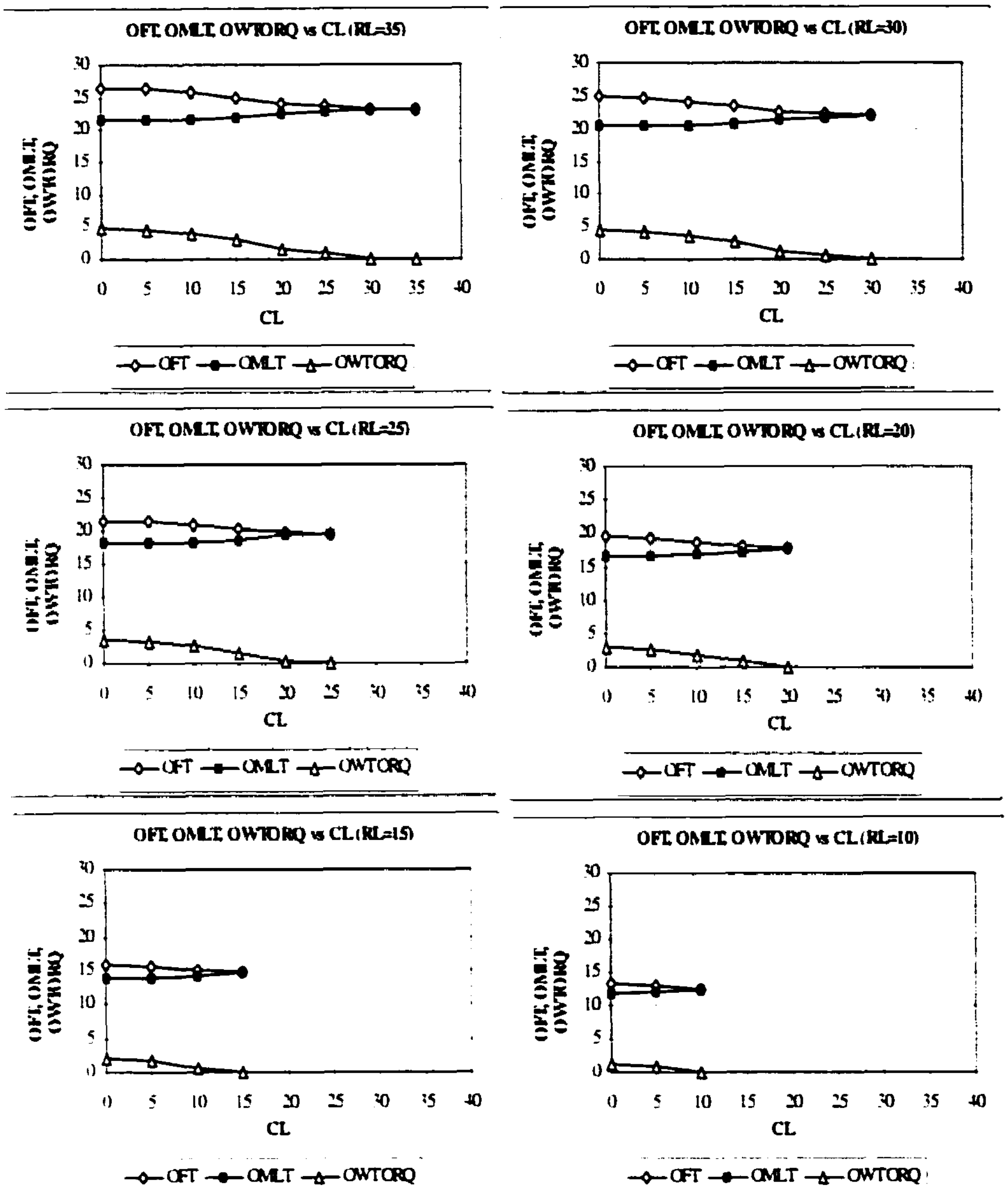

Figure 4.7: OFT, OMLT and OWTORQ vs. CL (for Different Values of RL)

4.4.1.3 <u>Effect on the Variability of Order Arrival into the ORQ and on the Variability of the Load in the ORQ</u>

Figure 4.8 depicts the effect of the control limits of the accept/reject rule and the order release rule on the variability (CoV) of the order arrival process into the ORQ and also on the variability (CoV) of the load in the ORQ.

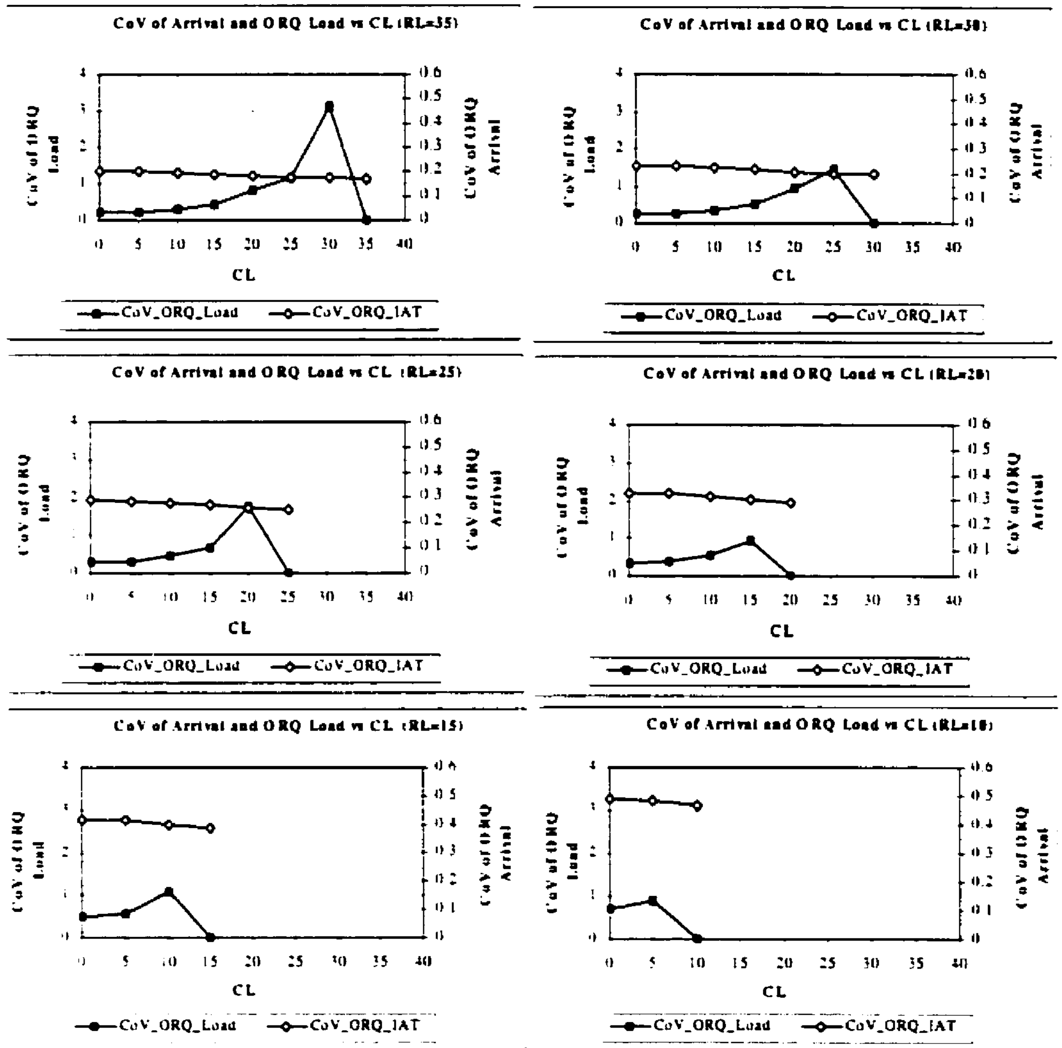

Figure 4.8: Variability of Inter-arrival Time to the ORQ and Load in the ORQ vs. CL (for Different Values of RL)

The following observations can be made from this experiment:

(a) At a particular value of RL_BUS, the CoV of the inter-arrival time of orders into the ORQ decreases with the increase of CL_BUSM,

(b) At a particular value of RL_BUS, the CoV of the load in the ORQ increases with CL_BUSM. Note that for all cases where RL=CL the CoV of the load in the ORQ is zero since these cases correspond to the immediate release.

(c) At a particular value of CL_BUSM, as RL_BUS decreases, the variability of both the quantities increase.

Regarding the variability in the load in the ORQ, it rises with CL_BUSM if RL_BUS remains at a particular value. The load level in the ORQ depends on the rate of load input to the ORQ (guided by RL_BUS, CL_BUSM and also the rate at which the shop floor processes the released load) and the rate of load release from ORQ (which is guided by CL_BUSM and the rate at which the shop floor processes the released load). When CL_BUSM is zero and RL_BUS is very high (which is equivalent to accepting all orders), the average load in the ORQ will be at its maximum (among all the possible combinations of RL_BUS and CL_BUSM) and the profile of the load in ORQ over time will remain close to this maximum. This happens because of the following reason. In the above situation, the rate of releasing the load from ORQ is lower than the rate of arriving candidate load (a portion of which is rejected) to the system. So whenever a portion of the load in the ORQ is released, the room thus created in the ORQ along one or more routes is filled up by arriving candidate load before more room is created in the same route(s) or other and this happens with a high probability. Thus the total load in ORQ remains high. Also, the load in ORQ cannot increase beyond the aforementioned maximum limit due to the presence of low CL_BUSM resulting in a low variability in the load in the ORQ.

4.4.1.4 Effect on the Variability of Overall Flow Time (OFT)

Figure 4.9 shows the effect of varying the control limits on the variability of flow time. The observations that can be made from this experiment are:

(a) At a particular value of RL_BUS, if CL_BUSM increases, the variability in OFT increases. The rate of increase gradually slows down at higher values of CL_BUSM.

(b) If RL_BUS changes, the change in variability of OFT depends on the combination of values of RL_BUS and CL_BUSM. At higher values of CL_BUSM the variability of OFT decreases with RL_BUS, while for CL_BUSM <= 15, the variability of OFT decreases with RL_BUS (from 35 backward in the figure) until RL_BUS = 20, after which the variability starts increasing with the decrease of RL_BUS.

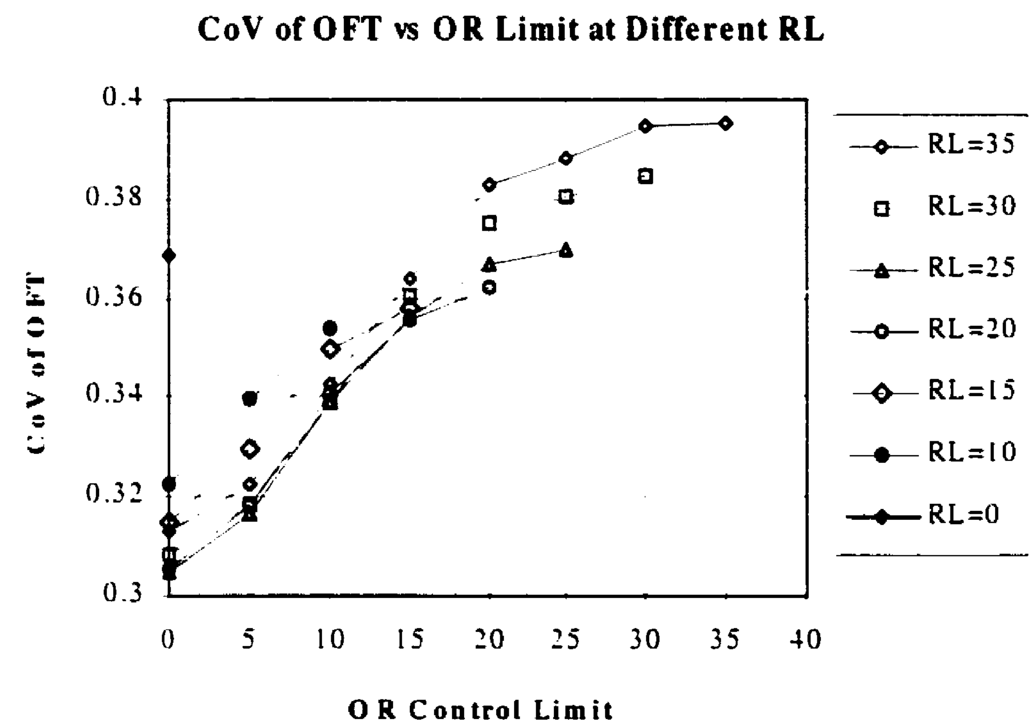

Figure 4.9: CoV of OFT vs. CL (for Different Values of RL)

4.4.2 Experiments Involving Both Regular and Urgent Orders

For these experiments, AR, OR and DR are varied through {TAL, BUS}, {TRL, BUSM} and {EDT, S/OPN} respectively and for each of these eight combinations of control rules relevant HL, RL and CL are varied through {10, 20, 30}, {10, 20, 30} and {10, 15, 20, 25, 30} respectively. Each of these experiments is carried out at the following specific values of the environmental factors, which are chosen to be their base level values.

DL	=	85%
DLV	=	0.1
PTV	=	0.1
PUO	=	5%
DDT	=	"Loose".

4.4.2.1 Experimental Approach

In order to avoid performing an excessively large number of simulation runs, instead of doing experiments according to a full factorial design, a different approach has been followed. Four regression models, one for each combination of AR and OR, have been built. Each regression model connects OPA and other relevant changing parameters (*i.e.* DR and relevant HL, RL and CL). From each of these regression equations, OPA can be predicted for different values of these changing parameters. For each of the regression equations, a cubic polynomial in DR, HL, RL and CL has been fit to the observed values of OPA from a specified set of experiments. It is assumed that a cubic polynomial will adequately represent the true relationship between OPA and those parameters. The set of experiments was chosen from a range of possible experiments (corresponding to a full factorial experimental design) by means of a D-optimal design (John and Draper, 1975) under the restriction that the effects considered (*i.e.* the terms appearing) in the regression equation can be estimated from this optimum (minimum) set of experiments. This D-optimal design was carried out using the SAS statistical software package. **Appendix G** provides a brief description of this approach.

However as a criticism of this approach it should be noted that this D-optimal design does not guarantee that these effects are estimated without confounding each other. As a result, the coefficients of the terms appearing in the regression equation may be biased. This means that, recognizing these coefficients as random, the expectation of these coefficients are not necessarily equal to their true value. However, (a) as this bias creeps in not only due to the incorrect experimental design to estimate these coefficients but also due to the incorrect choice of the postulated regression model (Draper and Smith, 1966) and, (b) as it is very complex to identify a *fractional* experimental design where all the chosen effects (appearing in the regression equation) can be estimated without confounding each other, it was decided to recourse to a D-optimal design.

A brief general introduction of the D-optimal design, a justification of the effects chosen in the regression equations, and the exact SAS program to generate one of these D-optimal designs (the others are similar) are given in the **Appendix G**.

4.4.2.2 Effect on OPA

Different values of HL, RL and CL (corresponding to appropriate AR and OR) as well as DR (whose possible values are EDT and S/OPN), are plugged into the regression equations thus obtained, to predict the value of OPA. The complete set of results is presented in tabular form in **Appendix H**. From the results the key observations are as follows:

(a) For any combination of AR, OR and DR, at any pair of values of HL and RL, OPA increases as CL increases,

(b) In the above experiments, the S/OPN rule performs better than the EDT rule, in all cases.

It has been observed in section 4.4.1.2 that holding orders in the order release queue always increases the average overall waiting time in the order release queue (OWTORQ) although it reduces the average overall manufacturing lead time (OMLT). Thus the benefit obtained by reduction of OMLT is offset by the increase in OWTORQ so that the OFT increases and as a result the system loses money through increased OPTL. This explains why OPA increases with the increase of the control limit of an order release rule. In other words, when

OPA is the principal performance measure to look at, it is always better to operate the system with immediate release (IMM) as the order release rule.

The results of the experiments suggest that using S/OPN as a dispatching rule is always better than EDT. This is because EDT gives priority to a job on the basis of its due date which is static in nature, while the criterion on which S/OPN works is based on a quantity which is equal to the slack per remaining number of operations. This latter quantity is dynamic in nature and is updated to its most recent value when the decision is taken. If two jobs, having equal due date, are competing for the same resource, then EDT will choose the one having the earlier entry time into the system, whatever may be its remaining slack per number of remaining operations. Also, there is no mechanism in EDT to handle jobs with negative slack. S/OPN handles these jobs on the basis of a cost criterion, while EDT keeps on prioritizing these jobs on the basis of due date which is inadequate in these situations.

Chapter 5

Main Experiments and Analysis

It has been observed in the preliminary experiments on the uncontrolled manufacturing system (*i.e.* when all orders are accepted and released to the shop floor immediately) how overall performance achievement (OPA) varies with the environmental factors. It has also been observed that for the environmental factors at their base levels, for any combination of AR, OR and DR, immediate release (IMM) is the best order release rule and S/OPN is the best dispatching rule as long as the principal performance measure concerned is OPA. In the remainder of this thesis further experiments will be restricted so that OR and DR are fixed at these levels. Thus the experiments reported in this chapter focus on the making of optimal accept/reject decisions.

The chapter begins with a study of how the main system performance measures vary with the control parameter(s) of the active accept/reject rule at different values of the environmental factors. The main focus of this chapter is on how different parameters of the accept/reject rules can be optimally chosen under different given values of the environmental factors. The sensitivity of this optimal choice of control parameters to variation in the environmental factors is also studied. Material is also presented comparing the performance of each AR rule (under optimal values of its control parameters) with the full acceptance case (*i.e.* when all orders must be accepted). The chapter concludes with a comparison of the performance of the three different accept/reject rules considered in this research.

Throughout this chapter, acronyms are used extensively to refer to the experimental factors and many performances of interest. Please see **Appendix D** for the acronym glossary.

5.1 The Effect of the Control Parameters of the Accept/Reject Rules on the Main Performance Measures

5.1.1 The BUS Accept/Reject Rule

To study the effect of the control parameters in the case of the BUS accept/reject rule on the main performance measures of the system at different values of the environmental factors, RL_BUS is varied through {14, 18, 22, 26, 30} hours with HL_BUS fixed at 22 hours. This is done when one of the environmental factors (*i.e.* DL, DLV, PTV, PUO or DDT) changes across different values while others are held fixed at their base levels. The values of these environmental factors used in this experiment are as follows (with the base levels shown in bold font):

DL = {0.75, **0.85**, 0.95},
DLV = {**0.1**, 0.55, 1.0},
PTV = {**0.1**, 0.3},
PUO = {**0.05**, 0.15, 0.25},
DDT = {"**Loose**", "Tight"}.

For each of the different scenarios, the system has been simulated for 5 replications each of length 83520 hours which includes a warm-up period of 11520 hours, so that a confidence interval on the average of each of the observed performance measures has a half width less than or equal to 0.1% of the mean value of the performance measure. The observed performance measures are OPA, UPA, RPA, OPRL and OPTL. **Figure 5.1** has been drawn with the environmental factors at their base levels. The figure shows that as RL increases

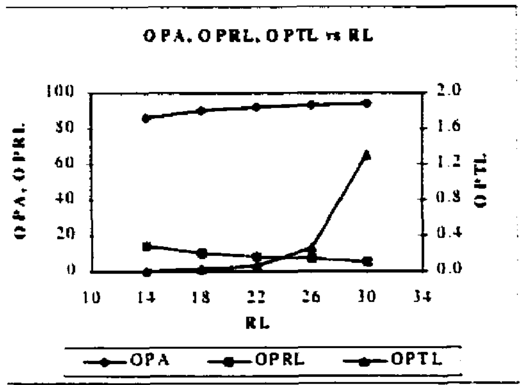

Figure 5.1: OPA, OPRL and OPTL vs. RL

OPA increases. The figure also shows how the corresponding OPRL and OPTL vary with increasing RL to yield the resulting OPA. As RL increases, OPTL increases while OPRL decreases. If RL increases further (which is not shown in this figure), OPA will eventually decline owing to the very high OPTL although OPRL will be very low. So for a fixed value of HL, there can be found a RL for which OPA is maximum where the total loss, comprised of rejection loss and tardiness loss, is the minimum for the given set of values of the environmental factors. Keeping other environmental factors at their base levels, if DL is varied, OPA is affected as shown in the **Figure 5.2**. Each of the three curves in the figure shows its convex nature but as DL increases the maximum value of OPA is achieved at lower value of RL, which means that at a high congestion the system will reject more orders to

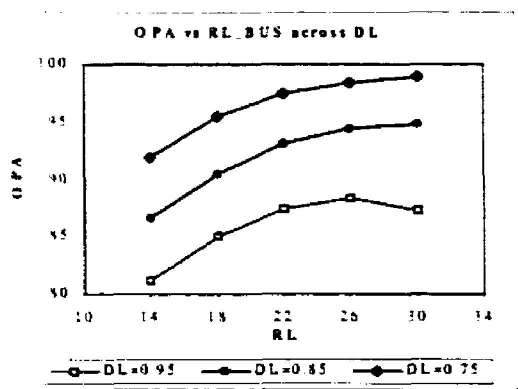

Figure 5.2: OPA vs. RL Across DL

reach the maximum OPA.

If OPRL and OPTL are plotted (as shown in **Figure 5.3** and **Figure 5.4**) for these three values of DL under the same conditions of Figure 5.2, then it can be observed that at a particular RL, both OPRL and OPTL are higher at a higher DL and as RL increases OPTL dramatically increases for higher DL. As the present system has a fixed capacity and the due

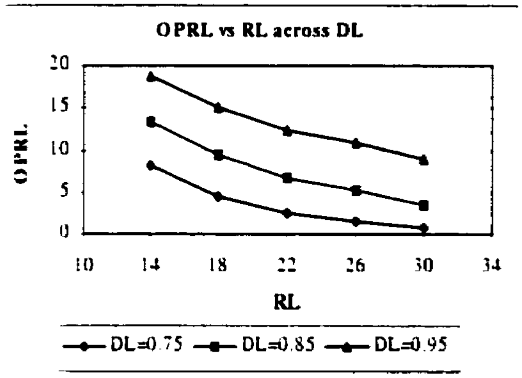

Figure 5.3: OPRL vs. RL Across DL

date of the orders cannot be influenced, at a higher DL the system achieves the maximum OPA by rejecting more orders (*i.e.* by lowering RL).

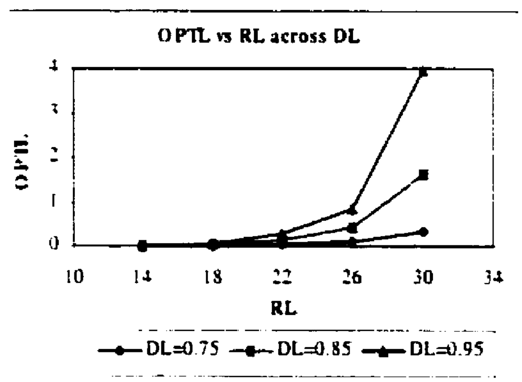

Figure 5.4: OPTL vs. RL Across DL

As DLV increases the value of OPA at a particular HL and RL decreases. This is shown in

Figure 5.5. This figure is drawn with other environmental factors at their base levels. The interaction effect of RL and DLV on OPA is insignificant in this particular scenario. As PTV increases a similar phenomenon is observed as is shown in **Figure 5.6**. In this case it can also be observed that at a higher PTV, the system tries to achieve the maximum OPA at a lower value of RL, other conditions remaining unchanged.

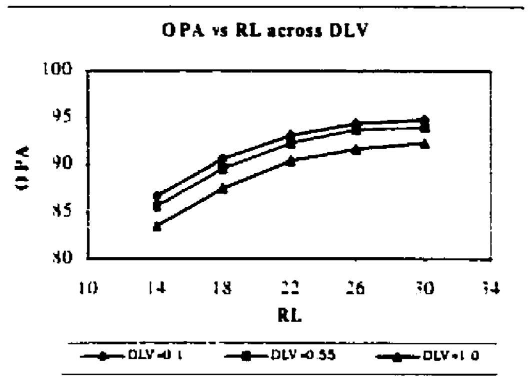

Figure 5.5: OPA vs. RL Across DLV

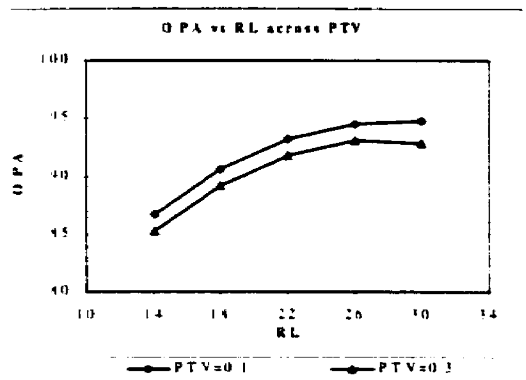

Figure 5.6: OPA vs. RL Across PTV

Figure 5.7 shows the effect of PUO on OPA under varying RL with the other environmental factors set at their base levels. At a lower RL, OPA is higher for higher PUO, whereas when RL is high the scenario with lower PUO will attain higher OPA.

The effects of varying DDT on OPA are shown in **Figure 5.8**. At the "Tight" level of DDT, OPA drops at a much faster rate with increasing RL and also the system tries to attain the optimum OPA at a lower value of RL. At the "Tight" level of DDT, the flow allowance of an order is smaller and also the tardiness cost penalty factor (*i.e.* Ktr) is higher. So to avoid a high tardiness penalty, the system rejects more orders to attain the maximum OPA which is achievable at that condition.

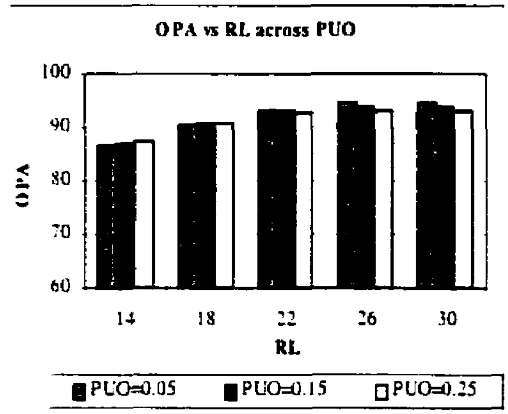

Figure 5.7: OPA vs. RL Across PUO

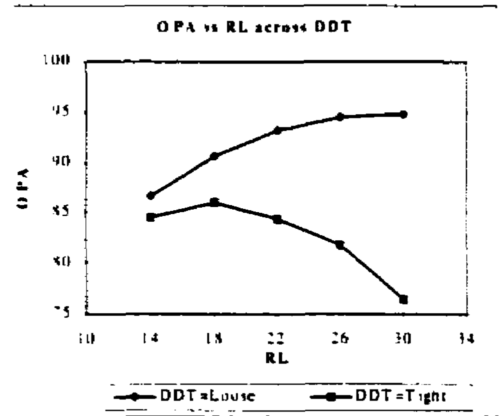

Figure 5.8: OPA vs. RL Across DDT

5.1.2 The TAL Accept/Reject Rule

To study the effect of the control parameters in the case of the TAL accept/reject rule on the main performance measures of the system at different values of the environmental factors, RL_TAL has varied through {50, 100, 150, 200, 250} hours with HL_TAL fixed at 50 hours. This is done when one of the environmental factors (*i.e.* DL, DLV, PTV, PUO or DDT) is varied over the same range of values as for the BUS rule in section 5.1.1. while others are held fixed at their base levels.

As for the BUS case, for each of the different scenarios the system has been simulated for 5 replications each of length 83520 hours which includes a warm-up period of 11520 hours, so that confidence intervals on the average of each of the observed performance measures have half widths less than or equal to 0.1% of the mean value of the performance measure. The observed performance measures are OPA, UPA, RPA, OPRL and OPTL. Plots corresponding to those for the BUS rule in 5.1.1. are given for the TAL rule in **Appendix K**. These plots which are hopefully self-explanatory, yield highly similar observations on how variation of the environmental factors and of the TAL rule's control limits affect performance. The only interesting observation that can be made in comparison to the BUS rule is that OPA is somewhat insensitive to increasing RL after a certain value of RL, within the range of RL chosen for this experiment. The plots indicate that OPA is less sensitive around the optimal value of the control limit, compared to the BUS rule. However this is not so in the case of a "Tight" level of DDT and in the scenario with DL = 0.95, in which case the slope around the optimum is comparatively much steeper.

5.2 Finding the Optimal Control Policy for Given Environmental Conditions

This section reports on an important and major aspect of this research which is to study how the system can be optimally controlled under different environments by adjusting the control parameters of the accept/reject rules. Also it is of interest to study how sensitive this choice of control parameter(s) is with respect to variation in the environmental factors. The following sections study this for each AR rule option. For each rule, two different cases *viz.* the case of all regular orders and the case of two classes of orders have been separately studied.

5.2.1 The General Approach to Finding the Optimum

To find out what should be the optimal policy *i.e.* what should be the value(s) of control limit(s) when a certain accept/reject rule is active, so that the system performs the best, the general approach taken is described below. This same approach is followed in all cases where the optimum is sought. This approach has two main steps:

(a) In the first step, a regression model is built which connects OPA and the controllable and environmental factors *viz.* HL, RL, DL, DLV, PTV, PUO (not present if all orders are regular) and DDT.

(b) After the regression model is built, OPA is optimized using this regression model with respect to HL and RL when other factors are set at specific values. The optimization is done by implementing the quasi-Newton search algorithm to find the direction of search while forward differencing is used to estimate the partial derivatives of the objective function. An initial estimate of the basic variables in one-dimensional search, is done by quadratic extrapolation. Optimization of this type can be carried out using the Microsoft Excel solver.

To build a regression equation, a cubic polynomial in six factors (when PUO is zero) or seven factors (when PUO is non-zero) is fitted to the observed values of OPA, which are obtained from a specified set of experiments. This set of experiments is determined by a D-optimal design (see **Appendix G** for more details on this technique) under the condition that the effects appearing in the regression model are estimable, although not necessarily without confounding each other. The criticism, assumption and the justification presented in the previous chapter is again valid here. In the case of BUS and TAL accept/reject rules when two classes of order are involved the set of experiments mentioned above (to build the corresponding regression model) was equivalent to a full factorial experimental plan.

Each regression model thus built, is stochastic in nature as the coefficients of the terms in the regression model are random. To optimize OPA with respect to HL and RL, it is required to find out the maximum of the expected value of OPA for all possible pairs of values of HL and RL (or Kincr in the case of the SIMUL AR rule). If a pair of values of these two control limits is plugged into the regression model, the value of OPA thus obtained is the expected value of OPA. So when the optimum OPA is determined using the optimization method as mentioned before, it is this expected value of OPA which is optimized. However when the optimization algorithm compares between two values of the objective function in the process of optimization, it does not consider the confidence interval around those expected values *i.e.* in other words, the algorithm assumes that the situation is deterministic.

To determine the quality of these regression models, the predictions for OPA at some specific sets of values of the environmental factors from each of the models have been compared with their corresponding values as obtained from the direct simulation of the system. This comparison is shown in **Appendix I**.

5.3 Optimal Control with the BUS as Accept/Reject Rule

5.3.1 The Case of All Regular Orders

These optimal values of RL_BUS are plotted in different figures which show how the optimal choice of the control parameters varies with different environmental factors. The plots corresponding to all the main effects and only strong two-way interaction effects among the environmental factors (as is obvious from the regression equation in the appendix) have been presented in the following sections.

5.3.1.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.9 shows how the optimal control limit varies with DL from 0.75 to 0.95 at a step of 0.05 keeping other factors at their base levels. From the figure it can be observed that as DL increases, RL decreases. At each value of DL, RL is chosen so as to give the most appropriate balance between rejection and tardiness costs that yields the overall best possible

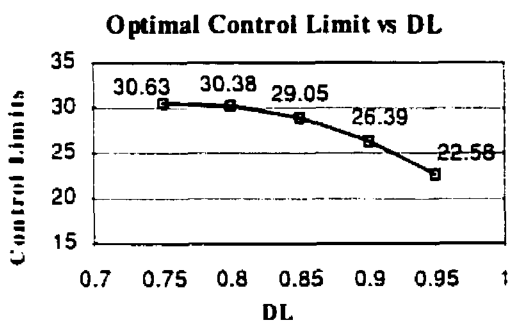

Figure 5.9: RL vs. DL (for BUS, PUO = 0%)

performance. Clearly, as DL changes, so does the balance point. When DL increases RL needs to be lowered further, otherwise too large a portion of the extra amount of arriving load (due to increased DL) will enter into the system, resulting in excessive congestion in the system.

5.3.1.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.10 shows how the optimal choice of the control limit is influenced by changing DLV when DLV is varied through 0.1, 0.35, 0.6, 0.85 and 1, while other factors are kept at their base levels. The plot suggests that as DLV increases beyond 0.35 the optimal value of RL increases. A possible justification for this is as follows. With increased DLV, for the same DL, the system encounters more intense peak load interspersed with deeper and wider troughs in load. However on average the system gets an opportunity to process surges in load during the following trough periods so that any tardiness penalties associated with a surge in load are smaller than they would be at a lower DLV. Thus the total loss is minimized by increasing RL.

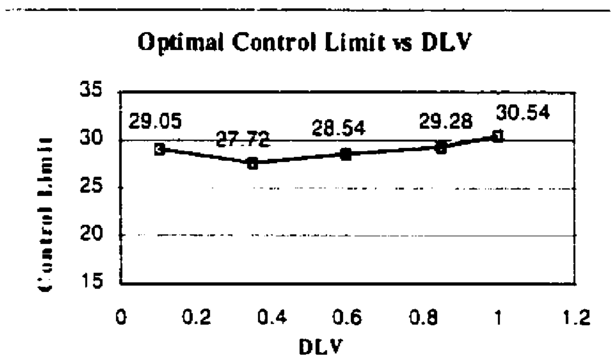

Figure 5.10: RL vs. DLV (for BUS, PUO = 0%)

5.3.1.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.11 was created by varying PTV through 0.1, 0.2 and 0.3 (while keeping other factors at their base levels) and shows how the optimal choice of the control limit is influenced by PTV. The results suggests that at this particular DL, RL decreases as PTV increases over this particular range.

As PTV increases, the uncertainty in the duration of the processing time of a task increases. This leads to more uneven congestion in the shop. Since the absolute error between the true load and the simple estimate of it (as the sum of mean task processing times) will be larger. Underestimating the load will cause more congestion in the system leading to more tardy loss, while overestimating the load will increase the rejection loss.

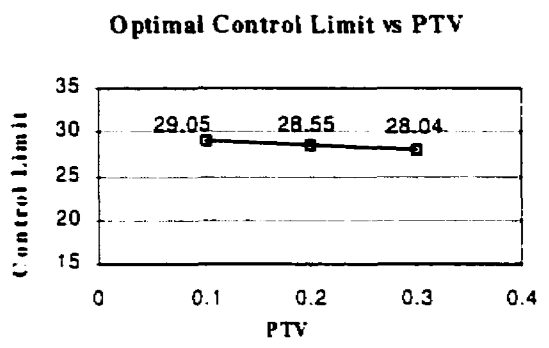

Figure 5.11: RL vs. PTV (for BUS, PUO = 0%)

A possible justification for the relationship suggested in the plot is as follows. When the system rejects an order all that is lost is the potential revenue of the order (*i.e.* the exact magnitude of the penalty is known) and as an indirect effect, the processing of the existing orders in the system and the orders which will be accepted in the near future are facilitated. On the other hand, if an order is accepted the maximum benefit that can be achieved is the earning of the maximum revenue of the order but there is a twofold risk associated with this. They are a direct risk of tardy loss for this order which can be more than the maximum potential revenue and an indirect risk which is the probable tardy loss due to the created stress (through increased congestion) in the processing of the existing orders as well as the orders that are going to be accepted in the system in near future. So if PTV increases (with DL or other factors unchanged) the system finds it more economic to reject more orders.

5.3.1.4 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.12 shows how the optimal choice of the control limit is influenced by changing DDT between "Loose" and "Tight" levels with other factors being kept at their base levels. It can be seen that RL decreases as DDT increases. The "Tight" DDT level indicates a short flow allowance and a steep tardiness cost rate which would lead to significant increase in tardiness costs, compared with "Loose" DDT at the same value of RL. As a result at the "Tight" DDT level, the system tries to reject more orders by lowering RL. This will increase the rejection loss but the total loss will be minimized with this arrangement.

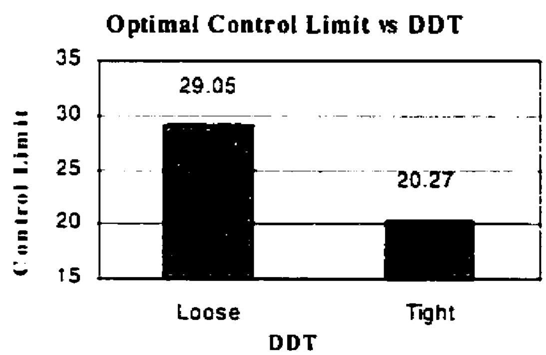

Figure 5.12: RL vs. DDT (for BUS, PUO = 0%)

5.3.1.5 Influence of DL under Changing DLV

Figure 5.13 shows how the optimal choice of the control limit is influenced by DL when DLV is also changing. One plot is included for each of five levels of DLV with each plot varying from 0.75 to 0.95 at a step of 0.05. The results suggest that at low DL, RL decreases as DLV increases, while at high DL, RL increases with DLV.

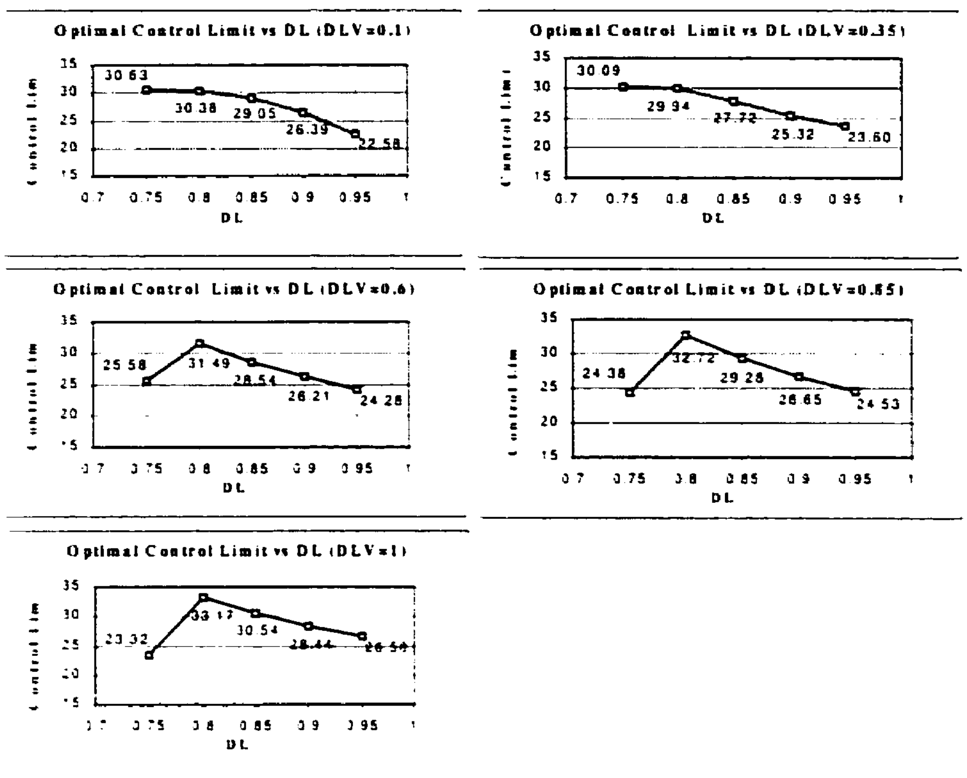

Figure 5.13: RL vs. DL under Changing DLV (for BUS, PUO = 0%)

5.3.2 The Case of Two Classes of Order

In the case of two classes of order, the values of HL_BUS and RL_BUS to optimize OPA at different values of the environmental factors are obtained as detailed earlier. These optimal values of HL_BUS and RL_BUS are plotted in a range of figures in the following sections to show all the main effects and only strong two-way interaction effects among the environmental factors.

5.3.2.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.14 shows how the optimal control limits vary with DL from 0.75 to 0.95 at a step of 0.05 keeping other factors at their base levels. It can be observed that (i) at DL = 0.75, RL is higher than HL, (ii) at a higher DL the system chooses HL to be higher than RL to operate optimally, and (iii) for DL within this higher range, HL does not vary much with DL while RL decreases as DL increases.

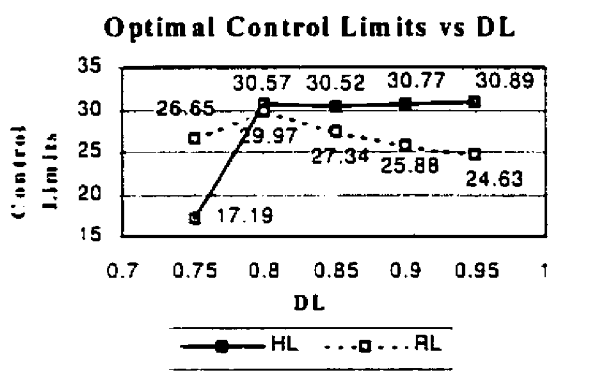

Figure 5.14: HL and RL vs. DL (BUS)

Possible justifications for these three observed phenomena are as follows.

(i) When the system chooses HL to be higher than RL for optimal operation, it in effect reserves some space for the anticipated future urgent orders by rejecting some regular orders. In this scenario, only 5% of arriving orders are urgent which makes the arrival of urgent orders relatively infrequent. So at a low DL of 0.75, reserving space for the urgent orders and thus rejecting the regular orders causes a rejection loss which is more than the extra revenue that could have been earned by accepting more urgent orders. So at DL = 0.75, to operate optimally, more regular orders are accepted by keeping RL greater than HL.

(ii) At DL greater than 0.75 however, the system shows a preference for the urgent orders over the regular orders. Here the system finds it beneficial to reserve some extra space for the urgent orders by rejecting some regular orders. The extra loss of revenue due to the rejection of regular orders (compared to the situation when HL=RL) is lower than the extra revenue earned by accepting more urgent orders. This acceptance of extra urgent orders would not have been possible, without excessively large increases in tardiness costs, if some extra regular orders were not rejected.

However this does not necessarily mean that all urgent orders are accepted. Accepting all urgent orders might increase the loss due to tardiness of both classes of orders. Due to the variability in the arrival process in the system there is an uneven frequency of arrival of urgent orders. If all the urgent orders are accepted by further lowering RL (and hence by rejecting more regular orders), during any period of low frequency of arrival of urgent orders, the loss suffered by the system due to the rejection of regular orders cannot be made up by the revenue earned even by all the urgent orders in this period. So the total loss will increase through the increased rejection loss. On the other hand if RL is not lowered further and all the urgent orders are accepted, this will lead to an increase in tardiness loss. So the optimum arrangement has been to reject a requisite amount of urgent and regular orders so as to minimize the sum total of the rejection and tardiness loss of both urgent and regular orders.

(iii) The system under consideration is a fixed capacity system and is working here under varying DL. To operate in an optimum fashion (*i.e.* producing the maximum OPA at a given situation), RL and HL must adjust to protect the system appropriately from the dynamics of the environment. Plots of OPRL and OPTL (see **Figure 5.15**) reveal that during the interval DL = 0.75 and 0.80, the system operates in an optimal fashion by accepting more orders while beyond that region, it relies on rejecting more orders. In this figure the values of OPRL and OPTL at a particular DL are plotted when the system operates optimally.

So beyond DL=0.80, the system treats orders of the two classes significantly differently. Rather it is apportioning the urgent and regular loads judiciously (through proper setting of HL and RL) to maximize OPA. The system will always try to accept urgent orders as much as possible (under the constraint that the total loss is minimized, as explained in the context of observation (ii)). As DL is increased the frequency of urgent orders will also increase and

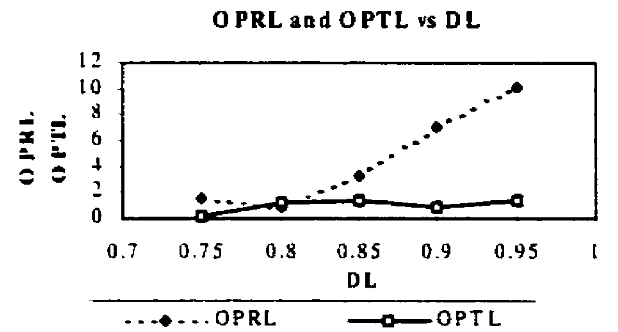

Figure 5.15: OPRL and OPTL vs DL (BUS)

the system will try to accept these extra urgent orders fully (see the plot of UPRL and RPRL in **Figure 5.16**, with the values corresponding to the optimal operation of the system), although on an overall basis the system will operate optimally by rejecting orders (leading to an increase in OPRL) which is achieved through rejecting more regular orders (and not the urgent orders). So RL will be reduced due to two reasons: (a) due to the increase in demand level (this has been already explained in the context of "all regular" case), and (b) in order to be able to accept extra urgent orders without causing overly large tardiness penalties.

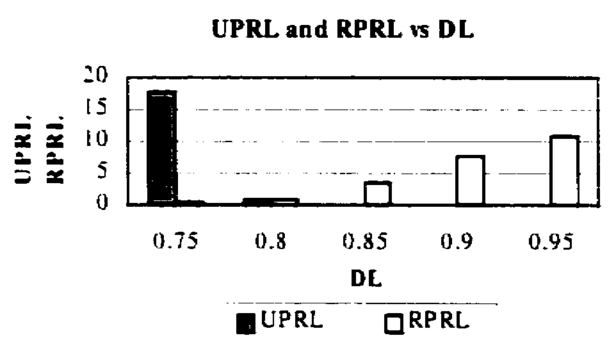

Figure 5.16: UPRL and RPRL vs. DL (BUS)

5.3.2.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.17 suggests that there is little influence of DLV on the choice of the optimal control limits when other factors are fixed at their base levels. **Figure 5.18** shows that the maximum values of OPA achievable at different DLVs do not vary significantly either. These values of OPA were obtained by simulating the system at the optimal values of the control limits with the environmental factors set at the values for which the Figure 5.17 has been drawn.

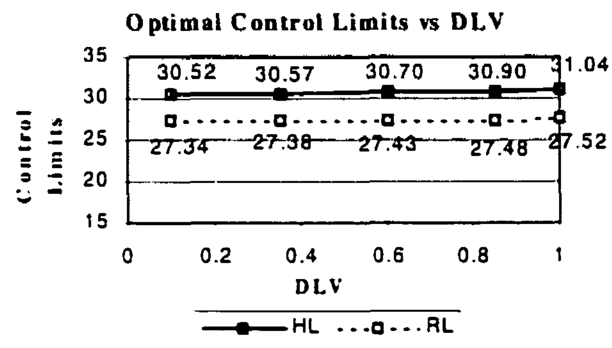

Figure 5.17: HL and RL vs. DLV (BUS)

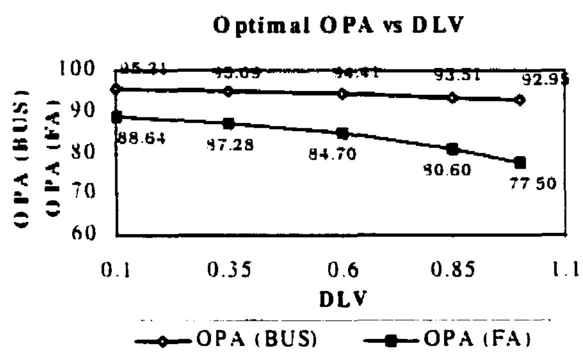

Figure 5.18: Optimal OPA vs. DLV (BUS, FA)

5.3.2.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.19 is created by varying PTV through 0.1, 0.2, 0.3 while keeping other factors at their base levels. It shows that varying PTV has little influence on the choice of the optimal control limits.

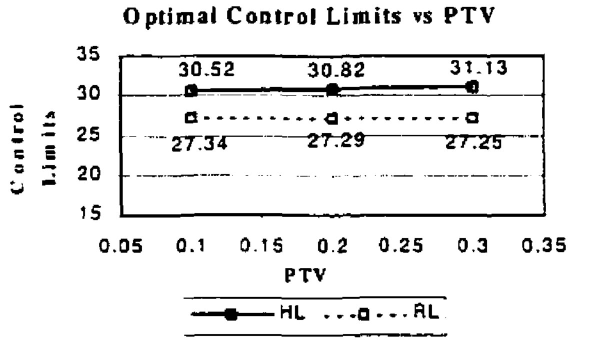

Figure 5.19: HL and RL vs. PTV (BUS)

5.3.2.4 Influence of PUO When Other Factors Are Fixed at Their Base Levels

Figure 5.20 shows how the optimal choice of the control limits is influenced by changing PUO from 5% to 25% at a step of 5% when other factors are fixed at their base levels. From the figure it can be observed that HL stays higher than RL over the whole range of PUO, and also that as PUO increases, HL remains relatively constant while RL decreases slowly.

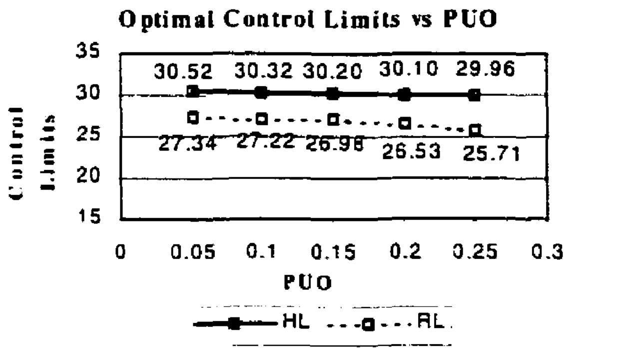

Figure 5.20: HL and RL vs. PUO (BUS)

To gain insight into this scenario, it is useful to look at the plots showing how OPA, OPRL, OPTL, UPRL, RPRL, UPTL and RPTL are varying with respect to PUO when the system is operating in an optimal fashion. These plots are shown in **Figure 5.21**. The necessary data for these plots were obtained by simulating the system with the control limits at their optimal values and the environmental factors set as for Figure 5.20.

The system finds it economic to keep space for the urgent orders and to do this a necessary amount of regular orders are rejected. Thus HL remains higher than RL. At DL = 85%, the system operates optimally by rejecting orders on an overall basis. If PUO is increased, the system accepts all the extra urgent orders and RL is lowered accordingly to reject the necessary quantity of regular orders so that the tardy loss does not become excessive.

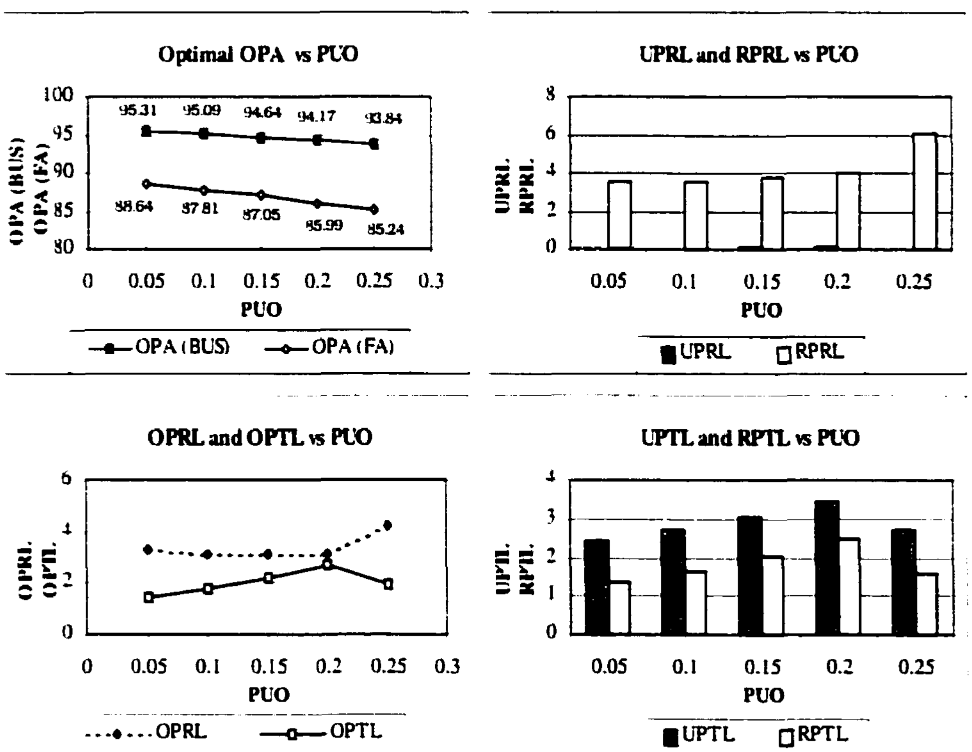

Figure 5.21: OPA, OPRL, OPTL, UPRL and UPTL vs. PUO (BUS)

5.3.2.5 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.22 shows how the optimal choice of the control limits is influenced by varying DDT across two different levels *viz.* "Loose" and "Tight" with other factors kept at their base levels. It can be observed that at the tight level, RL reduces while HL increases compared to the "Loose" level. This is expected because otherwise in the "Tight" level, the tardy loss will increase. So more orders are rejected. In both cases, HL remains higher than RL. When DDT level changes from "Loose" to "Tight", the corresponding OPA drops from 95.312 to 90.824. These values of OPA are obtained by simulating the system at the optimal values of the control parameters, with the environmental factors set at the values for which the Figure 5.22 has been drawn.

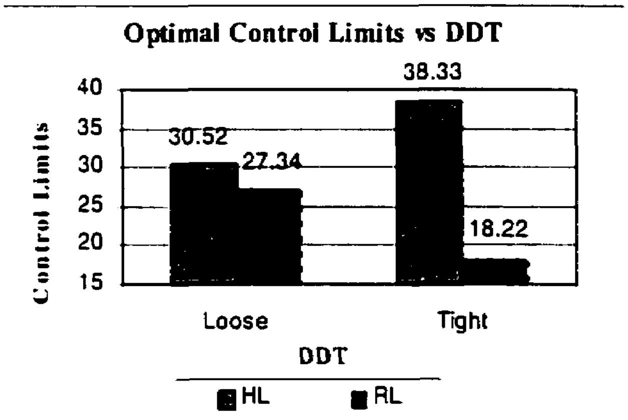

Figure 5.22: HL and RL vs. DDT (BUS)

5.3.2.6 Influence of DL under Changing DLV

Figure 5.23 shows how the optimal choice of the control limits is influenced by DL under changing DLV. From the figures it can be observed that other than for low DL at 0.75, both HL and RL are not very strongly affected by DLV.

An increase in DLV causes the system to encounter more intense peak load. When the system operates at DL = 0.75, the system is less congested and hence is able to accept this surge of load by increasing the control limits. So to operate optimally at a low value of DL, control limits increase with increasing DLV. This increase is not significant when the system operates at a higher DL.

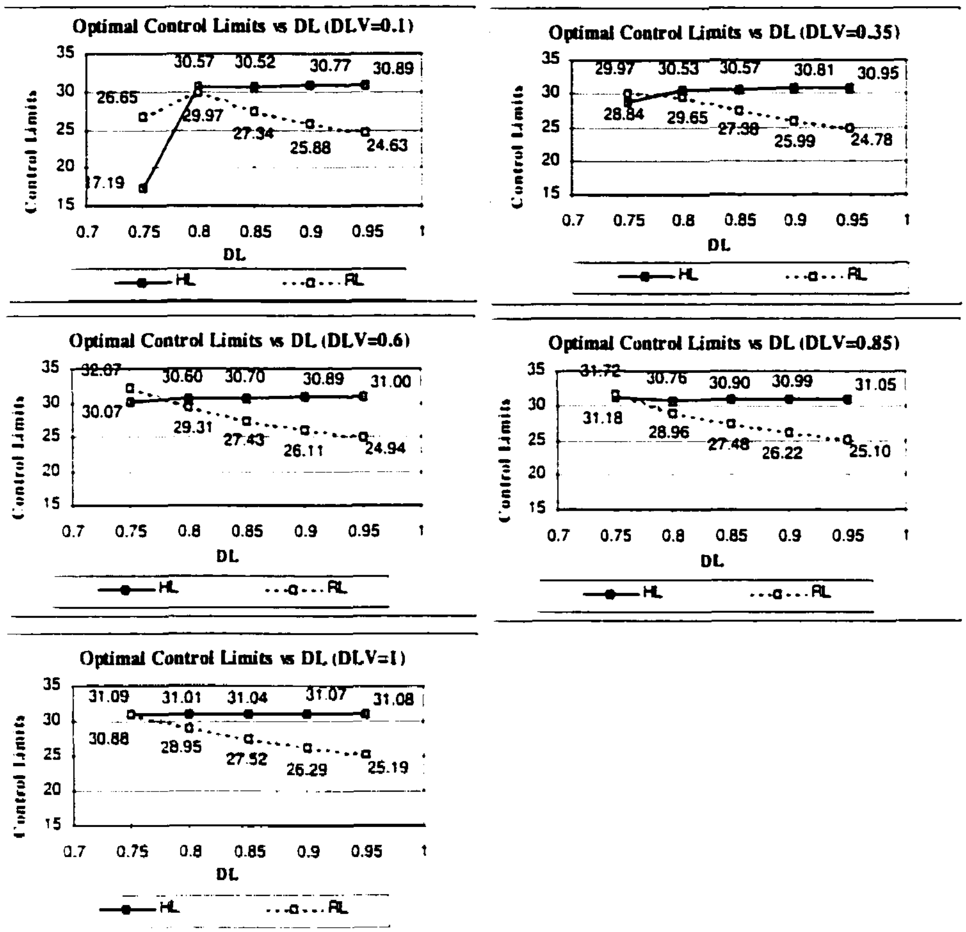

Figure 5.23: HL and RL vs. DL under Changing DLV (BUS)

5.3.2.7 Influence of DL under Changing PTV

Figure 5.24 shows how the optimal choice of the control limits is influenced by DL under changing PTV while keeping other factors at their base levels. Here also it can be observed from the figure that at a low value of DL (0.75), the optimal choice of both the control limits are affected strongly while at higher DL, HL increases and RL decreases very slowly, if they are sensitive at all to the change in PTV.

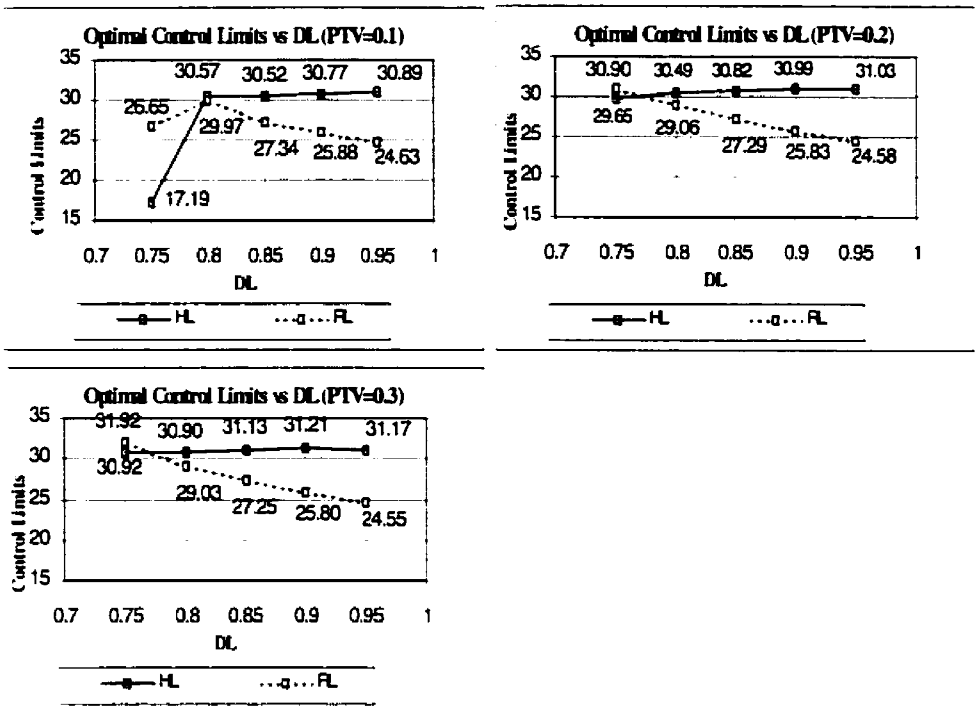

Figure 5.24: HL and RL vs. DL under Changing PTV (BUS)

5.3.2.8 <u>Influence of DL under Changing PUO</u>

Figure 5.25 shows how the optimal choice of control parameters is influenced by DL under changing PUO. It can be observed from the figure that at DL = 0.75, HL increases with increasing PUO, while at higher DL, both HL and RL are relatively insensitive to changing PUO.

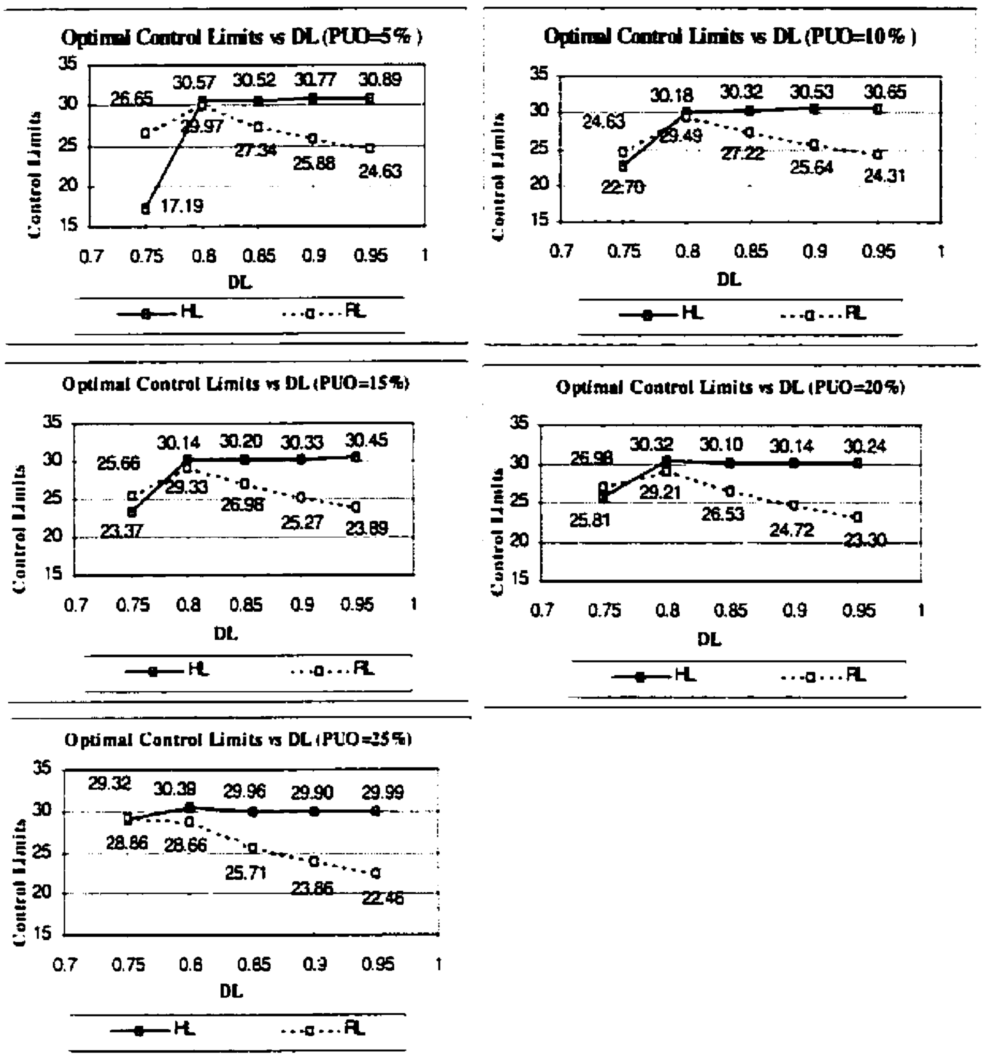

Figure 5.25: HL and RL vs. DL under Changing PUO (BUS)

5.3.3 Effect of Optimal Choice of HL and RL for BUS on the Main Performance Measures

In this section the effect of optimal choice of HL and RL on the main performance measures has been studied. The performance measures of interest include OPA, UPA, RPA, UxPA, RxPA, OPRL, RPRL, UPRL, RxPRL, UxPRL, OPTL, RPTL, UPTL, RxPTL, UxPTL. Each of these effects is observed and plotted when one factor in the environmental set is varied and the others are kept at their base levels. These plots have been presented in groups in **Appendix J**. Each such observation is obtained from a simulation run of the system when the control parameters are fixed at their corresponding optimal values while the environmental factors are set at the values at which the plot is drawn. The plots are self-explanatory as far as their identification is concerned. This section highlights only the key observations that can be made from these plots.

Figure 5.26 shows that as DL increases OPA drops significantly but performs much better than when the system accepts all orders. **Figure 5.27** shows that at low DL, OPRL decreases up to DL = 0.80, after which it increases significantly, showing that the system maintains

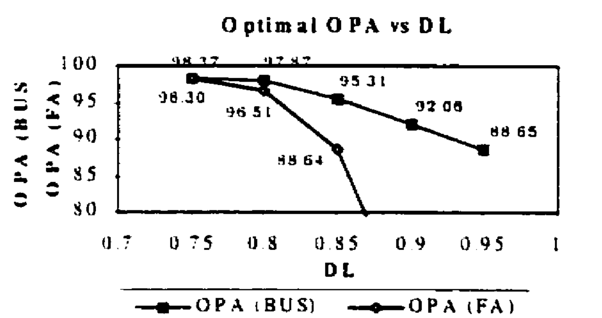

Figure 5.26: OPA vs. DL (BUS, FA)

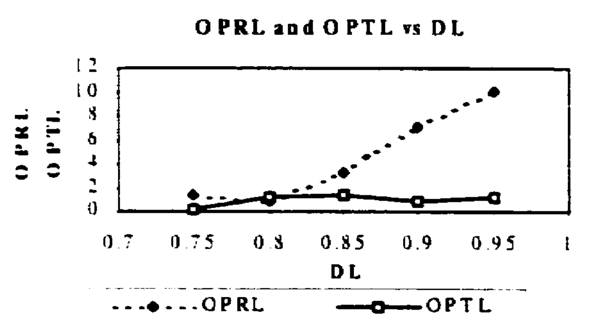

Figure 5.27: OPRL and OPTL vs. DL (BUS)

optimal performance by increasing the proportion of orders rejected. OPTL keeps low compared to OPRL all across DL >= 0.85. However when DLV, PTV or PUO increases, OPA drops very little compared to when DL changes. With increasing DL, UPA and RPA are appropriately adjusted as shown in **Figure 5.28**.

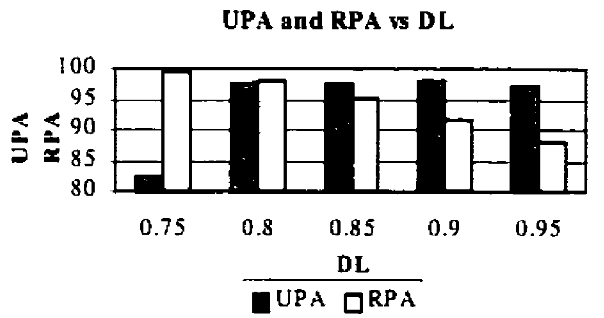

Figure 5.28: UPA and RPA vs. DL (BUS)

Figure 5.29 illustrates how different cost related terms vary with respect to DL under optimal control. Also **Figure 5.30** shows how the average total accepted shop load varies with DL under optimal control.

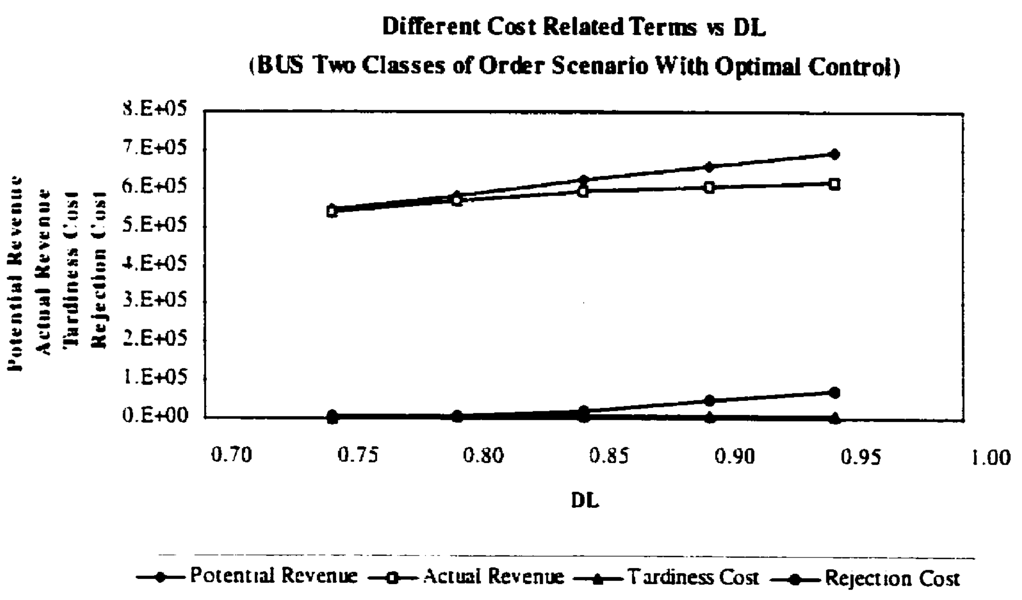

Figure 5.29: Different Cost Related Terms vs DL (BUS Two Classes of Order)

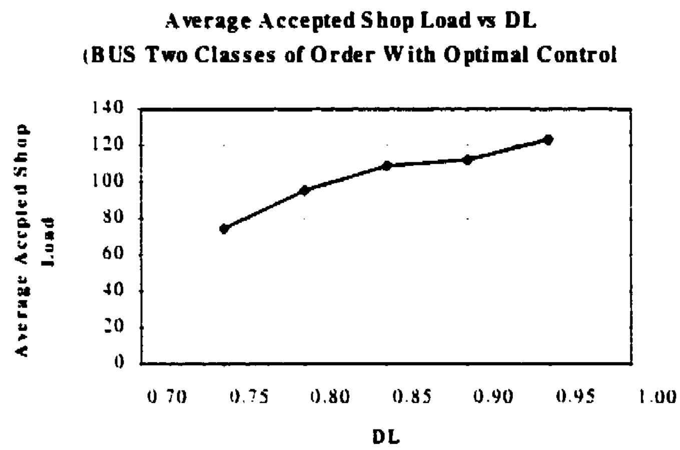

Figure 5.30: Average Accepted Shop Load vs DL With Optimal Control (BUS, Two Classes of Order)

5.4 Optimal Control with the TAL as Accept/Reject Rule

5.4.1 The Case of All Regular Orders

These optimal values of RL_TAL are plotted in different figures which show how the optimal choice of the control parameters varies with different environmental factors. The plots corresponding to all the main effects and only strong two-way interaction effects among the environmental factors have been presented in the following sections.

5.4.1.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.31 shows how the optimal control limit varies with DL over the range 0.75 to 0.95 at a step of 0.05 keeping other factors at their base levels. It can be seen that the choice of RL is insensitive to variation in DL.

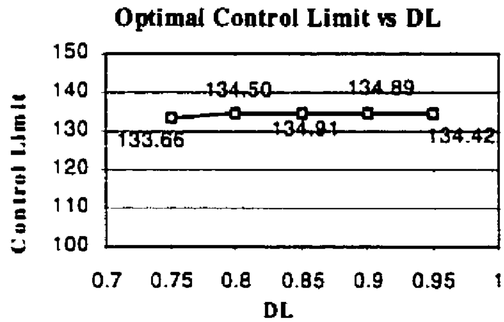

Figure 5.31: RL vs. DL (for TAL, PUO = 0%)

5.4.1.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.32 shows how the optimal choice of the control limit is influenced when DLV is varied through 0.1, 0.35, 0.6, 0.85 and 1, while other factors are kept at their base levels. It can be seen that RL increases with DLV. The possible justification for this is the same as that proposed in section 5.3.1.2.

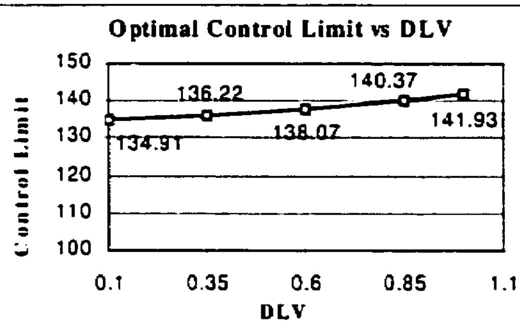

Figure 5.32: RL vs. DLV (for TAL, PUO = 0%)

5.4.1.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.33 shows how the optimal choice of the control limit is influenced when PTV is

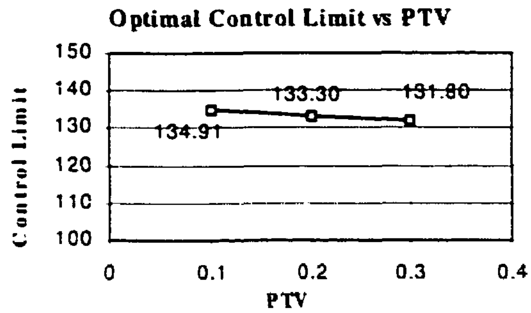

Figure 5.33: RL vs. PTV (for TAL, PUO = 0%)

varied through 0.1, 0.2 and 0.3, while keeping other factors at their base levels. The results show that RL decreases with PTV similar to the case when BUS was the AR rule.

5.4.1.4 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.34 shows how the optimal choice of the control limit is influenced when DDT is varied across two different levels *viz.* "Loose" and "Tight", other factors remaining at their base levels. It can be observed that RL decreases as DDT switches from the "Loose" to the

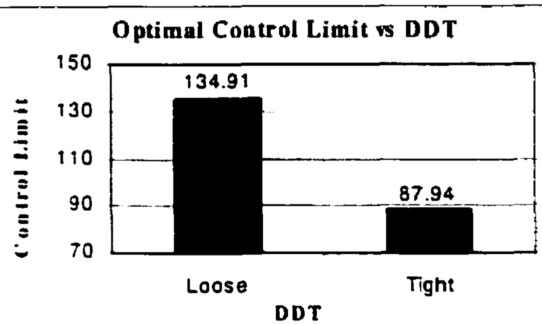

Figure 5.34: RL vs. DDT (for TAL, PUO = 0%)

"Tight" level. The system rejects more orders at the "Tight" level of DDT, to cope with the changed situation of smaller flow allowance and higher tardiness cost factor.

5.4.1.5 Influence of DL under Changing DLV

Figure 5.35 shows how the optimal choice of RL is influenced by DL over the range 0.75 to 0.95 at a step of 0.05 under changing DLV across the values 0.1, 0.35, 0.6, 0.85 and 1.0. It can be observed that at any particular DL, RL increases with DLV, but for a particular DLV, the optimal choice of control limits is relatively insensitive to the change in DL.

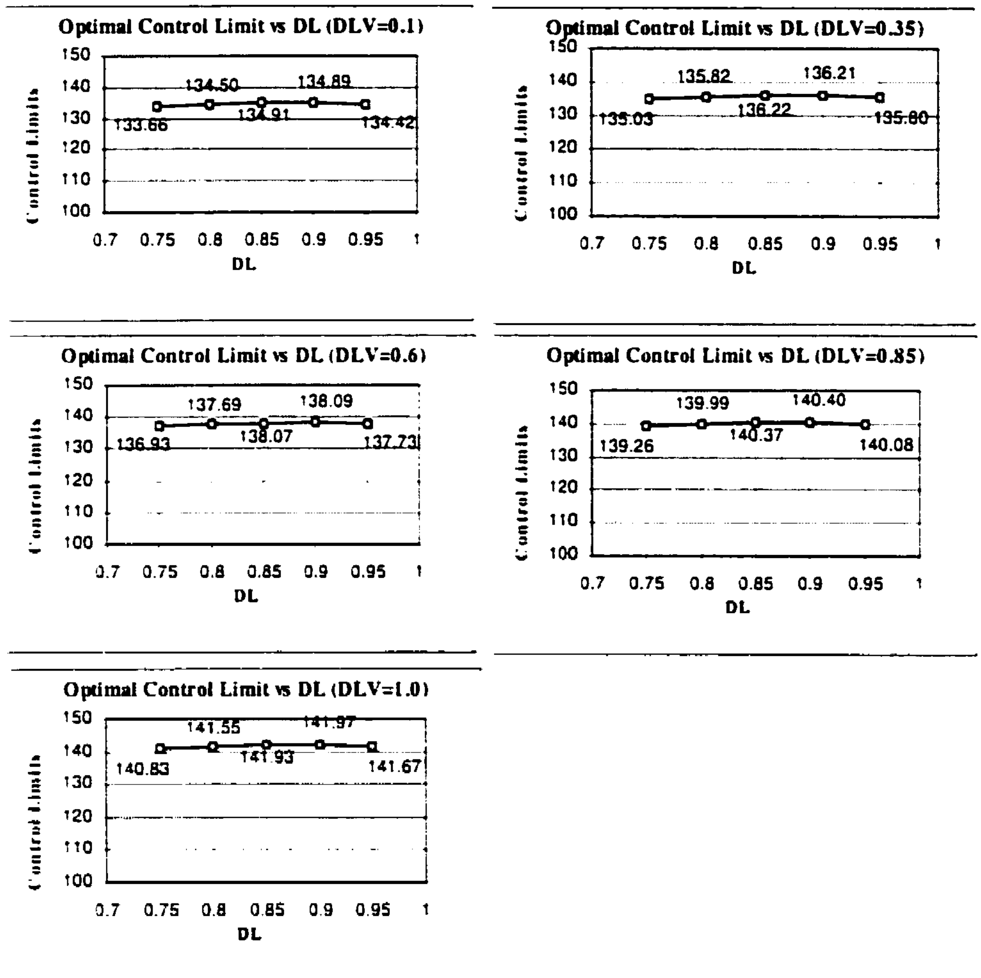

Figure 5.35: RL vs. DL under Changing DLV (for TAL, PUO = 0%)

5.4.1.6 Influence of DL under Changing PTV

Figures 5.36 shows how the optimal choice of RL is influenced by DL over the range 0.75 to 0.95 at a step of 0.05 under changing PTV across the values 0.1, 0.2 and 0.3. It can be observed that at any particular DL, RL decreases with PTV, but at a particular PTV the optimal choice is relatively insensitive to DL.

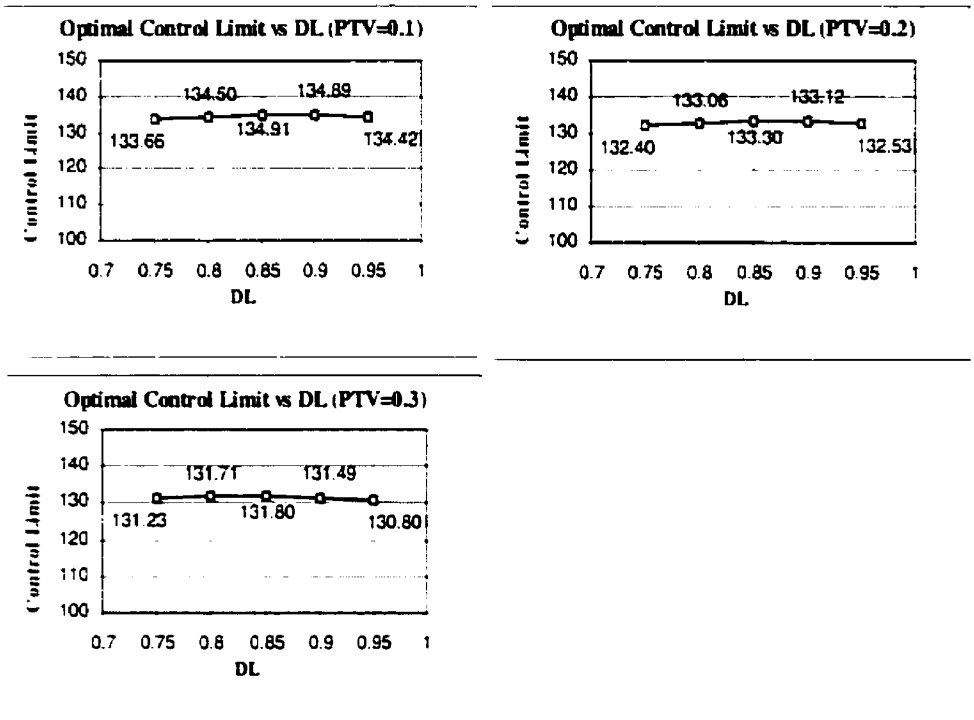

Figure 5.36: RL vs DL under Changing PTV (for TAL, PUO=0%)

5.4.1.7 Influence of DL under Changing DDT

Figures 5.37 shows how the optimal choice of RL is influenced by DL over the range 0.75 to 0.95 at a step of 0.05 under changing DDT between the levels "Loose" and "Tight". It can be observed that at the "Tight" level of DDT, RL dramatically goes down indicating that the

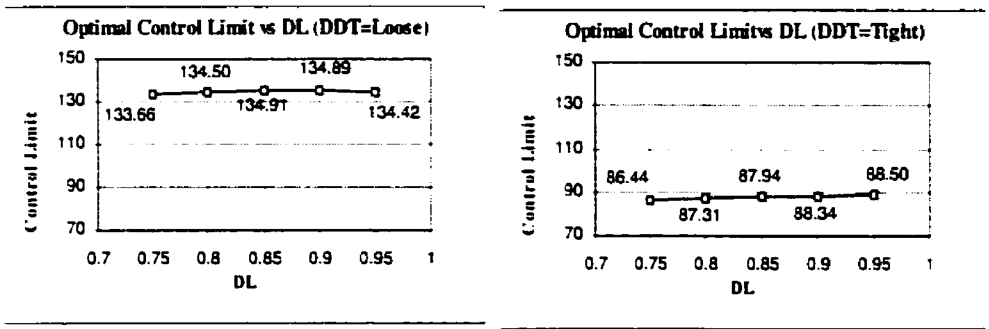

Figure 5.37: RL vs. DL under Changing DDT (for TAL, PUO=0%)

system rejects a large number of orders in the "Tight" level DDT compared to its "Loose" level.

5.4.2 The Case of Two Classes of Order

In the case of two classes of order, the values of HL_TAL and RL_TAL to optimize OPA at different values of the environmental factors are obtained as detailed earlier. These optimal values of HL_TAL and RL_TAL are plotted in a range of figures in the following sections to show all of the main effects.

5.4.2.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.38 shows how the optimal control limits vary with DL from 0.75 to 0.95 at a step of 0.05 keeping other factors at their base levels. From the figure the following observations can be made.

(1) RL decreases with increasing DL.

(2) HL increases up to DL = 0.80, then decreases with increasing DL.

(3) RL is higher than HL at any DL, but at higher DL their difference reduces.

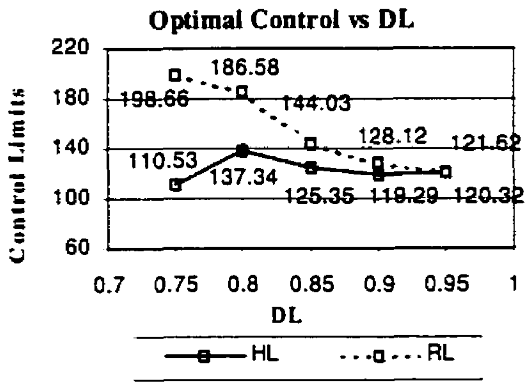

Figure 5.38: HL and RL vs DL (TAL)

5.4.2.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.39 shows how the optimal control limits vary with DLV across the values {0.1, 0.35, 0.6, 0.85, 1.0} keeping other factors at their base levels. From the figure it can be observed that there is little influence of DLV on the optimal choice of HL and RL. The

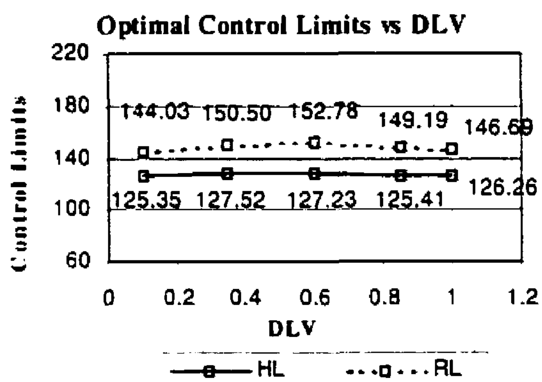

Figure 5.39: HL and RL vs. DLV (TAL)

values of OPA at these values of DLV with the respective optimal control limits are {92.68, 92.23, 91.53, 90.47, 89.63} respectively as obtained from simulation of the system at appropriate settings. These values show that OPA decreases slowly as DLV increases.

5.4.2.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.40 shows how the optimal control limits vary with PTV across the values {0.1, 0.2, 0.3} keeping other factors at their base levels. From the figure it can be observed that both RL and HL decrease with increasing PTV.

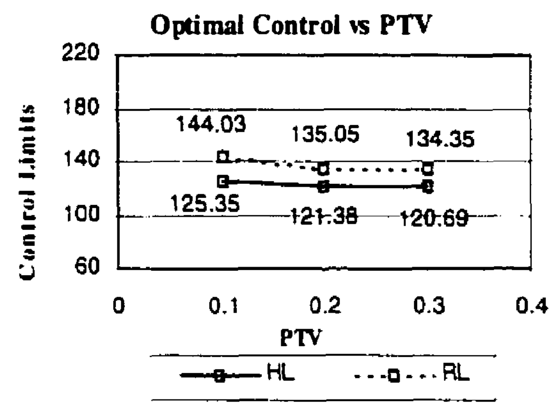

Figure 5.40: HL and RL vs. PTV (TAL)

5.4.2.4 Influence of PUO When Other Factors Are Fixed at Their Base Levels

Figure 5.41, shows how the optimal control limits vary with PUO across the values {0.05, 0.1, 0.15, 0.20, 0.25} keeping other factors at their base levels. From the figure it can be

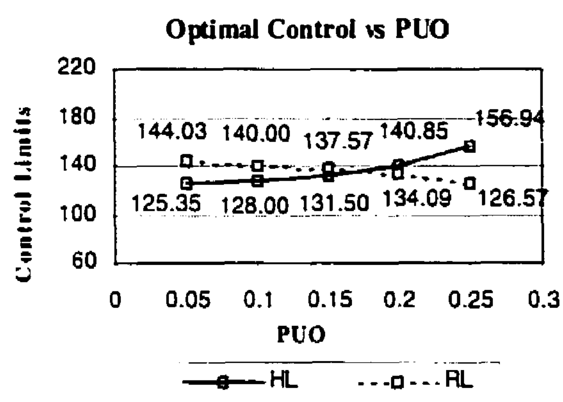

Figure 5.41: HL and RL vs. PUO (TAL)

observed that with increasing PUO, RL gradually decreases while HL increases.

5.4.2.5 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.42 shows how the optimal control limits vary with DDT across the levels {"Loose", "Tight"} keeping other factors at their base levels. It can be observed that, if the level of DDT is changed from "Loose" to "Tight", HL decreases while RL increases, RL always being greater than HL.

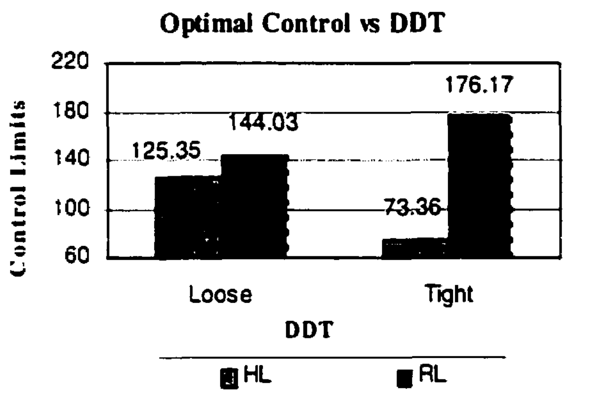

Figure 5.42: HL and RL vs. DDT (TAL)

5.4.3 Effect of Optimal Choice of HL and RL for TAL on the Main Performance Measures

In this section the effect of optimal choice of HL and RL on the main performance measures has been studied when TAL is the active accept/reject rule. These performance measures include OPA, UPA, RPA, UxPA, RxPA, OPRL, RPRL, UPRL, RxPRL, UxPRL, OPTL, RPTL, UPTL, RxPTL, UxPTL. Each of these effects is observed and plotted when one factor in the environmental set is varied while the others are held at their base levels. These plots have been presented in groups in **Appendix J**. Each observation in a plot is obtained from a simulation run of the system when the control parameters are fixed at their corresponding optimal values while the environmental factors set at the values for which the plot is drawn. These plots are self-explanatory as far as their identification is concerned. This section highlights only the most significant results evident from these plots.

When DL increases OPA is heavily affected but still remains better than the situation when the system accepts all orders. On the other hand if DLV, PTV or PUO is increased the maximum achievable OPA is comparatively less affected. Also in each case, the performance in terms of OPA remains better than that obtained in the corresponding full acceptance scenario. For performance in the full acceptance scenario, please refer to **Figure J.2.1** in **Appendix J**. When DL is above 0.80, OPRL rises dramatically while OPTL rises up to a certain limit and then remains stable. So with the increase of DL, the system operates optimally by rejecting more orders. In case of DLV also, as DLV increases, OPRL increases.

Except at very high DL (= 0.95), at all other levels of DL, RPA is greater than UPA. Also, except at low DL, the system performs better with larger regular orders as RxPA is better for larger x.

5.5 Optimal Control with the SIMUL as Accept/Reject Rule

5.5.1 The Case of All Regular Orders

Optimal values of *Kincr* are plotted in a range of different figures which show how the optimal choice of the control parameter varies with the environmental factors. Plots corresponding to all the main effects of the environmental factors have been presented in the following sections.

5.5.1.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.43 shows the influence of DL on the optimal choice of *Kincr* keeping other factors at their base levels. It can be observed that as DL increases *Kincr* increases which means that a larger proportion of arriving orders will be rejected.

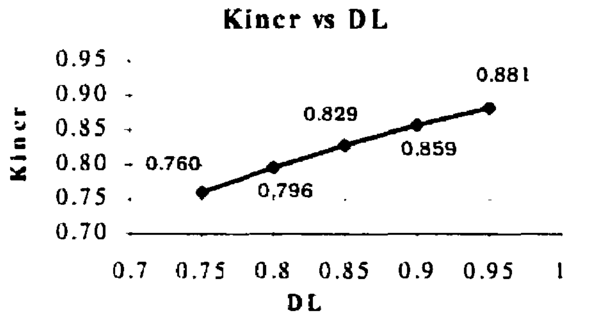

Figure 5.43: Kincr vs. DL (PUO = 0%)

5.5.1.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.44 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing DLV while other factors are kept at their base levels. It can be observed from the plot that as DLV increases *Kincr* rises up to a maximum before it drops again.

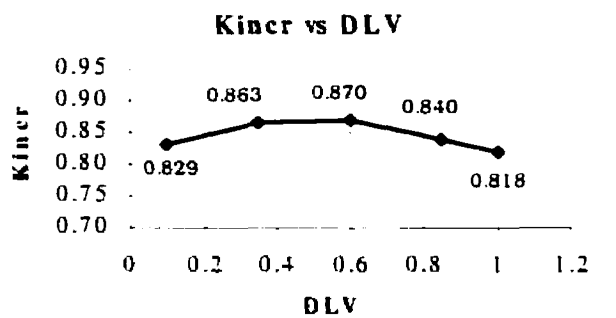

Figure 5.44: Kincr vs. DLV (PUO = 0%)

5.5.1.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.45 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing PTV while other factors are kept at their base levels. It can be observed from the plot that *Kincr* is insensitive to change in PTV.

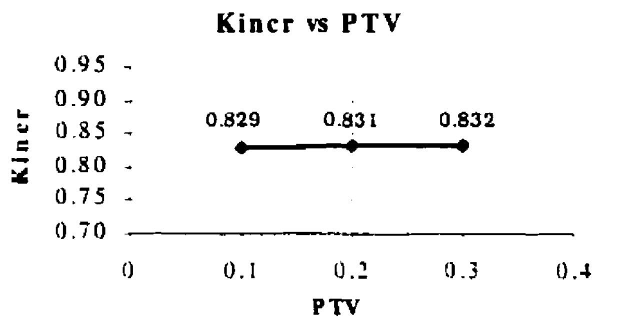

Figure 5.45: Kincr vs. PTV (PUO = 0%)

5.5.1.4 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.46 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing DDT. It can be seen that *Kincr* remains almost unchanged if DDT changes level from "Loose" to "Tight".

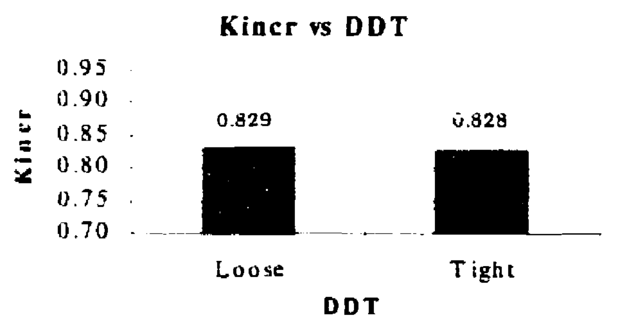

Figure 5.46: Kincr vs. DDT (PUO = 0%)

5.5.2 The Case of Two Classes of Order

These optimal values of *Kincr* are plotted in different figures which show how the optimal choice of the control parameters vary with different environmental factors. The plots corresponding to all the main effects have been presented in the following sections.

5.5.2.1 Influence of DL When Other Factors Are Fixed at Their Base Levels

Figure 5.47 shows how the optimal choice of control limit varies with DL from 0.75 to 0.95 at a step of 0.05 keeping other factors at their base levels. It can be observed that as DL is

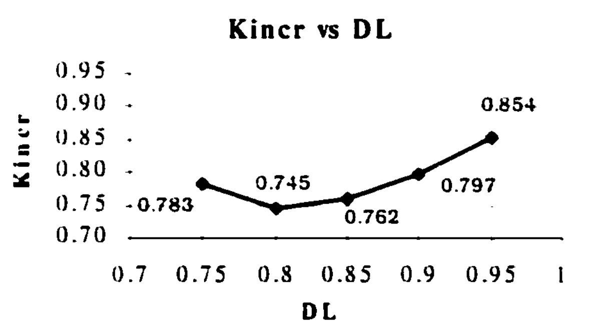

Figure 5.47: Kincr vs. DL (Two Classes of Order)

increased *Kincr* decreases to a minimum before it rises again. A transition from DL = 0.75 to DL = 0.80, accompanies an increased frequency of arrival of orders. The system accepts more orders (in absolute terms) in this new situation, because the system is capable of processing these extra orders over time and thus can improve the value of OPA. But beyond DL = 0.80, the system is not left with free capacity to process all further extra orders and hence the extra arriving orders due to increased frequency of arrival at higher DL, need to be rejected. Otherwise accepting those orders will increase the tardiness loss. So *Kincr* is increased beyond DL = 0.80.

5.5.2.2 Influence of DLV When Other Factors Are Fixed at Their Base Levels

Figure 5.48 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing DLV while other factors are kept at their base levels. It can be observed that, as DLV increases, *Kincr* reaches a minimum and then rises again.

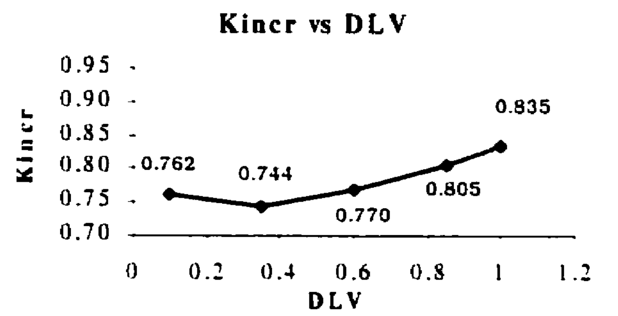

Figure 5.48: Kincr vs. DLV (Two Classes of Order)

5.5.2.3 Influence of PTV When Other Factors Are Fixed at Their Base Levels

Figure 5.49 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing PTV while other factors are kept at their base levels. It can be observed that, with the increase of PTV, *Kincr* increases. As PTV increases the uncertainty in the time to finish a task increases. The system tries to reject more orders to prevent excessive tardiness penalty.

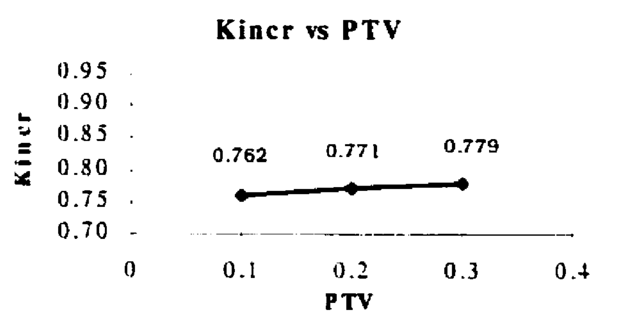

Figure 5.49: Kincr vs. PTV (Two Classes of Order)

5.5.2.4 Influence of PUO When Other Factors Are Fixed at Their Base Levels

Figure 5.50 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing PUO when other factors are fixed at their base levels. It is observed that *Kincr* increases with increasing PUO.

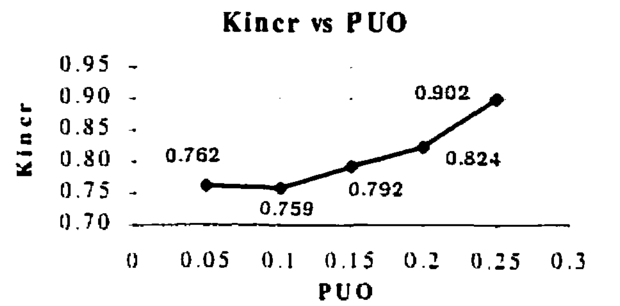

Figure 5.50: Kincr vs. PUO (Two Classes of Order)

5.5.2.5 Influence of DDT When Other Factors Are Fixed at Their Base Levels

Figure 5.51 shows how the optimal choice of the control limit (*Kincr*) is influenced by changing DDT with other factors kept at their base levels. It is observed that as the system transits from "Loose" to "Tight" DDT. *Kincr* increases.

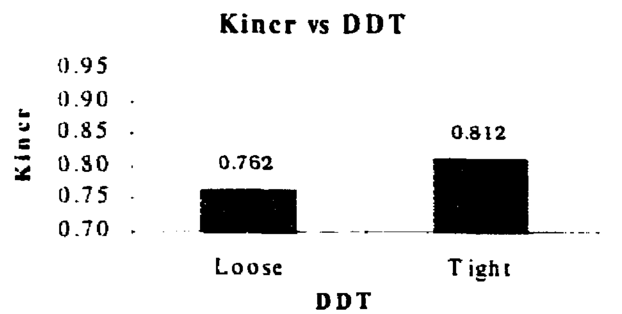

Figure 5.51: Kincr vs. DDT (Two Classes of Order)

5.5.3 Effect of Optimal Choice of *Kincr* on the Main Performance Measures

In this section the effect of optimal choice of *Kincr* on the main performance measures has been studied when SIMUL is the active accept/reject rule. These performance measures include OPA, UPA, RPA, UxPA, RxPA, OPRL, RPRL, UPRL, RxPRL, UxPRL, OPTL, RPTL, UPTL, RxPTL, UxPTL. Each of these effects is observed and plotted when one factor in the environmental set is varied and the others are held at their base levels. These plots have been presented in groups in **Appendix J**. Each observation in a plot is obtained from a simulation run of the system when the control parameters are fixed at their corresponding optimal values while the environmental factors set at the values for which the plot is drawn. These plots are self-explanatory as far as their identification is concerned. This section highlights the most significant observations from these plots.

If DL increases OPA goes down dramatically. OPA seems to be relatively insensitive to varying PUO, DLV or PTV. When each of these environmental factors increases OPRL increases with a moderate slope, while OPTL decreases or remains stable. The SIMUL rule performs better for the urgent orders with a lower number of steps at any value of the environmental factors. Please see **Figure J.3.2** in **Appendix J**.

Under SIMUL, the system rejects urgent orders with a higher number of steps more than the urgent orders having fewer steps at any DL, PTV or PUO. But at higher DLV, urgent orders with fewer steps get rejected more than the urgent orders with higher number of steps, as UxPRL is higher in this situation, for lower value of x. Rejection of regular orders is very low everywhere.

When the system is operating under SIMUL, it always has UPRL higher than RPRL at any condition of the environmental factors.

5.6 Comparison of the Performances of the BUS, TAL and SIMUL Rules

This section compares the performance of the three accept/reject rules that have been considered in this thesis on the basis of OPA, the principal performance measure of the system, as obtained from simulation runs. The comparison has been made when each environmental factor varies on its own at the following chosen levels (high, medium and low) with other factors held fixed at their base levels and also at some specific combinations of factor levels with other factors again fixed at their base levels. For each scenario, the manufacturing system was controlled optimally so that the maximum possible performance is achieved at that scenario. The chosen levels for each factor are as follows:

$$
\begin{aligned}
DL &= \{0.75, 0.85, 0.95\},\\
DLV &= \{0.1, 0.6, 1.0\},\\
PTV &= \{0.1, 0.2, 0.3\},\\
PUO &= \{0.05, 0.15, 0.25\},\\
DDT &= \{\text{"Loose"}, \text{"Tight"}\}.
\end{aligned}
$$

While doing this comparison IMM and S/OPN are the chosen values for OR and DR respectively as before.

Each simulation was run for 5 replications and the resulting 5 values of OPA were subjected to paired t-test to compare their means. The means are shown in **Table 5.1**. Except for scenarios (15), (16), (18) and (19), the mean OPA for BUS, TAL and SIMUL are always significantly different. The mean OPA for BUS and SIMUL, in the above four scenarios are not statistically different.

It can be observed from the table that BUS is the accept/reject rule which yields the best performance for almost all scenarios considered in the table. Except in scenario (1) when DL is very low and in scenario (6) when DLV is very high, BUS performs better than either of

TAL or SIMUL. In scenario (1), at low DL, TAL outperforms the other two, while at high DLV, SIMUL performs the best. SIMUL invariably performs better than TAL at any situation considered above except at very low DL.

Table 5.1: Comparison of Accept/Reject Rules Based on OPA

Scenario (Other factors are at base levels)	BUS		TAL		SIMUL		Best Rule
	HL, RL	Avg. OPA	HL, RL	Avg. OPA	Kincr	Avg. OPA	
(1) DL=75%	17.19, 26.65	98.36	110.53, 198.66	99.05	0.783	98.83	TAL
(2) DL=85%	30.52, 27.34	95.41	125.35, 144.03	92.63	0.762	94.90	BUS
(3) DL=95%	30.89, 24.63	88.77	121.62, 120.32	83.60	0.854	87.75	BUS
(4) DLV=0.1	30.89, 27.34	95.41	125.35, 144.03	92.63	0.762	94.90	BUS
(5) DLV=0.6	30.70, 27.43	94.58	127.23, 152.78	91.61	0.770	94.05	BUS
(6) DLV=1.0	31.04, 27.52	92.79	126.26, 146.69	89.62	0.835	93.20	SIMUL
(7) PTV=0.1	30.89, 27.34	95.41	125.35, 144.03	92.63	0.762	94.90	BUS
(8) PTV=0.2	30.82, 27.29	94.75	121.38, 135.05	91.99	0.771	94.09	BUS
(9) PTV=0.3	31.13, 27.25	93.68	120.69, 134.35	90.73	0.779	93.01	BUS
(10) PUO=5%	30.89, 27.34	95.41	125.35, 144.03	92.63	0.762	94.90	BUS
(11) PUO=15%	30.20, 26.98	94.65	131.50, 137.57	91.84	0.792	94.44	BUS
(12) PUO=25%	29.96, 25.71	93.79	156.94, 126.57	91.09	0.902	92.88	BUS
(13) DDT=Loose	30.89, 27.34	95.41	125.35, 144.03	92.63	0.762	94.90	BUS
(14) DDT=Tight	38.33, 18.22	90.75	73.36, 176.17	73.41	0.812	86.39	BUS
(15) DL=95%, DLV=1	31.08, 25.19	86.56	140.66, 133.22	81.78	0.875	86.56	BUS/ SIMUL
(16) DL=95%, PUO=25%	29.99, 22.46	86.81	125.84, 123.23	81.87	0.877	86.76	BUS/ SIMUL
(17) DL=95%, DDT=Tight	40.13, 16.14	84.45	72.92, 91.43	72.36	0.812	79.54	BUS
(18) DLV=1, PUO=25%	30.56, 25.65	90.91	158.7, 138.07	88.29	0.877	90.94	BUS/ SIMUL
(19) PTV=0.3, PUO=25%	30.59, 25.14	91.80	149.35, 126.84	88.78	0.858	91.62	BUS/ SIMUL

Chapter 6

Conclusions and Future Research

This chapter summarizes the main results of the experimental work reported in this thesis as well as highlighting the primary original contributions of the research. It concludes with a list of potential directions for future research that emerge from the work reported in this thesis.

6.1 Summarizing the Main Results From the Research

This section summarizes the main results obtained from this research, organized into four subsections each of which corresponds to one of the specific objectives of the research given at the end of Chapter 2.

6.1.1 Accept/Reject Rule Behaviour

The experiments reported in Chapters 4 and 5 have provided insight into the operation of an accept/reject rule under different environmental conditions. In general, as the severity of the pressure on a manufacturing system to meet delivery dates increases, so the accept/reject rule will need to increase the proportion of orders rejected (by changing its control parameters) in order to avoid excessively large tardiness penalties. Thus, typically a rule's rejection limit will need to change to cause the proportion of orders rejected to increase as any of the following environmental factors increase: demand level, system variability (in terms of either demand or processing times), due date tightness.

Some specific results from the experiments that are worth repeating here include the following:

(a) The results show that for the BUS accept/reject rule, under any set of values for the environmental factors, it is always possible to find an appropriate set of values for the limits on the accepted urgent and regular load on the busiest machine on the route of the order (*i.e.* HL and RL) for which the Overall Percent Achievement (OPA) is maximized.

(b) When there is only regular orders, an increase in the process time variability causes a reduction in the optimum value of RL at which OPA is maximum. However, the effect of increasing the demand level variability on the optimal value of RL seems to be the opposite, *i.e.* at increased variability in demand level, the value of RL at which the system attains the maximum OPA increases.

(c) When demand level is low, both for BUS and TAL accept/reject rules, the accepted load limit for the regular orders is set higher than that of the urgent orders to show preference for the regular orders. But for higher demand levels, the system always prefers urgent orders when working under BUS, although when working under TAL, the system does so only at the highest demand level. When demand level increases, the maximum OPA always drops whether working under BUS or TAL, while the net revenue increases monotonically.

(d) When the percent of urgent orders increases, the system always prefers to accept more urgent orders than regular ones when working under BUS, but it does not do so until the percentage of urgent orders is sufficiently high (more than 20% when other environmental variables are at their base level), when working under TAL.

(e) Under changing variability in the demand level or in the processing time, the system does not show appreciable sensitivity towards the choice of optimal control parameters for either of the BUS or TAL rules.

(f) When the due date tightness level switches from "Loose" to "Tight", the system, when working under the BUS rule, starts rejecting more regular orders than before to make space for accepting more urgent orders than before.

(g) BUS was tested with an order release rule (BUSM) other than immediate release (IMM) to experiment with a two-stage input control. It was found that holding orders in a pre-shop pool in the present manufacturing system deteriorates the overall performance achievement. Holding an order in an order release pool increases the system flow time, although the manufacturing lead time definitely reduces. It also increases the variability in the load in the order release queue. The experiment also showed a very complex effect on the variability of overall flow time when studied by varying the acceptance limit and the release limit of the rules.

6.1.2 Performance of the Simulation-based Accept/Reject Rule

The SIMUL rule as designed was able to perform significantly better than the base case of full acceptance but the results showed that for many environmental conditions this rule did not perform as well as the BUS algorithmic rule.

(a) The situations where the SIMUL rule was the best of the rules tested include those with high variability in the demand level (DLV = 1.0) and also with extremely high demand level (DL = 0.95), with other environmental factors set at their base levels. In these scenarios SIMUL was marginally better than BUS and substantially better than TAL.

(b) In Chapter 5, at some chosen sets of values of the environmental factors the three accept/reject rules have been compared on the basis of OPA. At situations other than high variability, the performance of SIMUL is close to that of BUS and almost 7% better than the full acceptance case.

(c) In two order class scenarios, at any level of an environmental factor while keeping other factors at their at their base levels, the system working under SIMUL rejects a higher proportion of urgent orders than that of regular orders to operate optimally.

(d) At any demand level, the system operating under SIMUL always achieves higher percent achievement for those urgent orders which have a smaller number of steps.

6.1.3 Optimal Choice of Accept/Reject Rule Control Limits

The method used to optimally choose rule control limits as a function of the manufacturing system's environmental factors involved the development of an appropriate regression model for each of the three rules for each of the scenarios "regular-orders only" and "two classes of order". For each of the six resulting cases, an appropriately chosen set of simulation runs was performed to provide the necessary data to allow a regression model to be constructed then a mathematical optimization engine was used to choose the control limits for each set of values of interest for the environmental factors.

The method implemented to determine the optimum value of the control parameter(s) and to predict the performance measure of the system at an arbitrary set of values of the environmental factors is generic in nature. The only restriction being that the input set of values of the environmental factors has to be within the range in which the regression model is valid. The input data set from which regression model is built should be chosen in such a way so that the variance of prediction from the regression model is minimized. This is where D-optimal design is useful which determines a subset from a candidate data set, so that the regression model built on that subset can predict with the minimum variance. In using this approach it is important that the observed values of the performance measures which are used to build the regression model should have very low bias, *i.e.* if they are found from simulation runs, it should be ensured that these are obtained from a sufficiently long run.

Among the six regression models built in this research to find the optimum value of the control parameter(s), the two models dealing with SIMUL accept/reject rule could not be validated. The reason for the poor quality of these two models is that the values of OPA at the chosen data points used to build the regression models were obtained from short simulation runs, due to the limited scope of resource that was available. The computers used to run these simulations (using SIMUL as the accept/reject rule) are very slow and their down time is very high. So within the time constraint, it was not feasible to get better estimates of OPA at the chosen points. The test results for accuracy for each of the six models have been provided in **Appendix I**.

For the BUS and TAL rules, the value of OPA around the optimal choice of the control parameters is not very sensitive to small variations in the rule control limits.

6.1.4 Accept/Reject Rule Behaviour When There Are Two Classes of Order

The experiments reported in Chapters 4 and 5 have provided insight into how an accept/reject rule performs when two classes of orders are present. As the results show, as the situation becomes more stressful, in terms of the difficulty of meeting due dates, so the rules start to treat the classes of order differently in terms of rejecting a higher proportion of "regular" orders as compared to "urgent" orders.

When two classes of order are involved, at low demand level the system working with the BUS accept/reject rule prefers regular orders more than the urgent orders, but at high demand level the system prefers urgent orders more than regular orders. In the case of the TAL rule, over all demand levels, the system prefers regular orders unless the percent of urgent orders is high in which case the system will prefer urgent orders. When working with SIMUL, at any value of any one of the environmental factors while keeping other environmental factors at their base levels, the percent rejection loss through urgent orders is always greater than that through regular orders.

6.2 Applicability of This Research in Practice

Regarding the applicability of this research in practice the following two aspects need to be considered. Firstly, it is necessary to identify which of the lessons learnt from this research might be applicable to other manufacturing systems in general. Secondly, what different aspects should be considered when attempting to implement the concept of order rejection in a real manufacturing organization.

The present research was carried out in a setting of make-to-order manufacturing systems. A make-to-order manufacturing system in practice might differ from the present hypothetical system significantly in terms of shop floor configuration, process plan of the orders, categories of orders, arrival process, occurrence of uncertain events (*e.g.* machine breakdown), etc. The results obtained in this thesis depending on these factors will not be valid in general and they are specific to this system. However, the results other than these should hold good in other make-to-order manufacturing systems as well.

More specifically it should be universally true that if demand level, demand level variability, process time variability, percent of urgent orders, severity of due date tightness increases any real manufacturing system will need to reject more orders on an overall basis in order to operate optimally.

On the other hand, all the categorical results, based on order class or number of steps involved in the order or based on the combination of these two, will heavily depend on the configuration of the shop floor, process plan of different orders and also the cost structure involved in the system. So these results cannot be generalized or directly applied to other systems.

However, the concept of judiciously rejecting some orders can be implemented in a specific real manufacturing system in an appropriately customized way. In general, this would require the construction of a simulation model to mimic, to a sufficient level of detail, the operation of the system. Next, this model would need to be exercised to develop a regression model capable of choosing the best rule, and the best control limits for that rule, as a function of the system's environmental factors. Finally data collection on and analysis of the operation of the real system would be required to estimate the values of these environmental factors, after which these could be input to the regression model so that the optimal control policy could be identified. Ongoing monitoring of the real system could be used to detect any significant changes in the environmental factors which would allow the control scheme to be adjusted if warranted.

6.3 Original Contributions

The present research includes several original contributions in the area of input control:

(a) The first contribution of this research is the development and testing of a simulation-based accept/reject rule which has been shown to outperform traditional algorithmic accept/reject rules in certain situations. This simulation-based accept/reject rule is able to take advantage of the capability of discrete-event simulation to predict the impact of alternative courses of action. This is the first ever reported application of discrete-event simulation to decide upon the acceptance/rejection of an arriving order.

Furthermore, this simulation-based accept/reject rule is a cost-based rule, which makes a decision on the basis of comparing estimates of the financial impact of the two alternative courses of action. This is also the first time that such a cost-based criterion has been used to make accept/reject decisions.

(b) Another contribution of this research is the introduction of the concept of adjusting the control limits so that in any given changed environment the system can perform optimally. Previously in all other research where rejection of orders has been considered, the control was not adjusted to optimize the performance of the system for that situation. This research also explored in detail how sensitive the optimal choice of accept/reject rule control parameters is with respect to variation in the environmental factors.

(c) This research has helped develop greater insight into how a manufacturing system with the ability to reject jobs behaves and performs under different environmental conditions. The experimental work carried out has lead to a better understanding of the impact of the accept/reject rule parameters both on overall system performance and on secondary performance measures of interest.

(d) This research has also developed insight into how such systems behave in the case of two classes of order. The experimental work has illustrated how the accept/reject rules treat the two order classes differently in order to maximize the overall performance of the system under different conditions.

6.4 Future Research

Based on completion of the work reported in this thesis, a number of potential directions for further research have been identified and are listed below:

(1) The development and testing of more sophisticated algorithmic accept/reject rules. Other variants of the load based algorithmic rules could be implemented. One such rule is to accept an order if the accepted load on the route of the order is less than some limit.

In the BUS accept/reject rule, an order is accepted if the accepted load on the busiest machine on the route of the order at the time of arrival of the order is below a chosen limit. The way this accepted load on the busiest machine on the route of the order is calculated (see section 3.2.1) makes the BUS rule, which uses this load information, biased. This is because the accepted load on a machine is generally variable over time. So if an order is accepted according to BUS, then it is possible that, during its sojourn through the system, the order may not actually experience that amount of load because a part of that load is processed in parallel by the busiest machine before the job in question actually arrives at that machine. Also, the job in question might be processed before a portion of the load arrives to the busiest machine. In either case the job is not affected by the load that was anticipated. So there are occasions when the load on the busiest machine is thus overestimated. This overestimate causes some orders to be rejected which otherwise could have been accepted. So the algorithmic rule BUS can be improved by introducing correction factors when using different load information at the time of order arrivals.

(2) Improvement of SIMUL to remedy a current flaw. SIMUL is another accept/reject rule where there is a scope for improvement. In the case of the SIMUL accept/reject rule, the pilot simulation runs are deterministic and also the future order stream is shut off during these pilot simulation runs. This will obviously affect the selection procedure. As the future orders are not allowed during the pilot simulation runs and these pilot runs are terminated only when the system is empty, the jobs in the system towards the end of the run will be finished faster due to less congestion in the system and thus the profit measure at the end of the pilot runs will be biased high. So the decision on the order acceptance on the basis of these performance measures will possibly be incorrect. Deterministic pilot simulation runs will also cause the decision to deviate from the correct one.

During the simulation run while future jobs are disallowed, statistics on the tardiness of a completed job could be collected in the following way.

$$Tardiness = Max(0,\ c(t) + Completion\ Time - Due\ Time),$$

where, $c(t)$ is a function of time which increases with t monotonically and acts as a compensating factor. The idea behind using this compensating factor is that when new arrivals are stopped and the rest of the jobs in the system are allowed to finish, they will be finished at a faster rate as the time advances, because there will be less and less congestion. So the monotonically increasing compensating factor $c(t)$ is an attempt to correct for this phenomenon. Here the challenge lies in the suitable determination of the function $c(t)$.

Also, during the pilot simulation runs, if the future orders were to be allowed then the orders need to be accepted according to an order accept/reject rule. Ideally this should be the same as SIMUL. In a pilot simulation however, if an order is accepted or rejected by SIMUL, it will lead to an infinite recursive loop which logically does not terminate. So it is not possible to implement SIMUL during the pilot simulation. This is an intrinsic functional problem in SIMUL. Further research is needed to alleviate these problems.

(3) Managing multi-class customers through selective order acceptance is another area where the current research could be extended to address a number of possible questions including:

(i) What should be the relevant control of the system to maximize the performance of the system at any situation?

(ii) How does providing a high service level to a relatively small group of high priority customers (which means all urgent orders are accepted and are hopefully serviced on time) impact the service of the remaining customers?

(iii) How much of a shop's workload can consist of high priority orders before the performance of the shop on the low priority orders deteriorates to an unacceptable level?

(iv) How can a manager provide excellent service to the lower priority customers at an acceptable level?

(4) Some of the assumptions involved in the current models could be relaxed so that input control in more realistic environments could be studied. Further work could include machine break down and unreliability, more complicated product structure (*e.g.* assemblies, orders for set of components *etc.*), labor constraints *etc.*

(5) The work could be extended to explore scenarios where other options than outright order rejection are considered. This could include:

(i) identification of the minimum overtime that would eliminate, or at least significantly reduce, the amount of orders rejected,

(ii) allowing the manufacturer and the customer to negotiate an alternative flow allowance, and perhaps order price.

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Appendix A

Definitions of Terms Used in the Literature

This appendix defines different terms and acronyms used in this thesis, especially in connection with the literature review in Chapter 2. Most of the items listed below fall into one of the following categories: schedule performance measures; accept/reject rules, order release rules; dispatching rules.

$\overline{D}$: This performance measure has been used by Irastorza and Deane (1974). It identifies the deviation of aggregate shop load for each machine (*i.e.*, total work in the shop) from a specified target set up by management. The deviation obtained for each machine is then averaged over all periods.

AGGWNQ : AGGWNQ is an order release rule used by Melnyk and Ragatz (1989). The release is initiated when the total incomplete work load in the shop falls below a minimum level. The selection of the jobs to be released is based on the least work in the next queue rule. This approach represents a 'shop-based' triggering mechanism in a combination with a 'global-selection' rule.

BFL : This order release rule works with a time horizon that is broken into time buckets and maintains a current work load profile for each machine in the shop. Working backward from the job's assigned due date. BFL attempts to fit each operation into available capacity for the appropriate machine. If adequate capacity is not available in a time bucket, it tries to fit the operation at an earlier bucket until adequate capacity is available.

BIL : There are several variations of this order release rule. But basically, some multiple of expected processing time or queue time is subtracted from its due date to calculate the release date. If the release date is on or before the current date, the job is released immediately to the shop regardless of current shop load. Otherwise the job remains in the pre-release queue until the release date. The BIL technique utilizes one of the following methods to calculate release date:

(1) $RD_i = DD_i - k_1 n_i$

(2) $RD_i = DD_i - k_1 n_i - k_2 Q_i$

where, DD_i = Due date of the job,

n_i = Number of operations in the job,

Q_i = Number of jobs in the queue of the machines on the job's routing,

k_1, k_2 = planning factors.

CR : This is a dynamic due-date oriented dispatching rule, which can take several forms. All of them determine the priority value of a job as a ratio of some measure of the expected amount of time left until the job's due date. This ratio is calculated in Ragatz and Mabert (1988) as:

$$CR = (DD - CT)/(RPT + RNO \times QAPO)$$

where, CT = current time,

DD = job due date,

RPT = remaining processing time for job,

RNO = remaining number of operations,

$QAPO$ = queue allowance per operation.

EDD : This dispatching rule calculates the loading priority of a job in a queue on the basis of the earliest due date.

FCFS : This dispatching rule calculates the loading priority of a job in a queue on the basis of the earliest entry time in the queue.

FFL : This order release rule assigns jobs to machines while taking into account the unassigned capacity at each machine. As machine capacity is fully assigned, jobs are assigned capacity further into the future until all operations have been scheduled. If this forecasted flow time is less the remaining time until the job's due date, release to the shop may be delayed and the flow time recalculated after the delay period. Release dates can also be based on total current shop loading or the projected future shop load over the expected flow time of the job, allowing orders to be released as soon as the actual or projected shop load (or bottleneck machine load) falls below some stated maximum allowable load.

IMM : See NORR.

IMR : See NORR.

MIL : This order release rule is the same as the variation (2) of BIL.

MINSLK : This dispatching rule calculates the loading priority of a job in a queue on the basis of the minimum slack.

MNJ : According to this order release rule, at the start of each period, the highest priority jobs are released to the shop floor, one at a time, until either all jobs are released or the number of jobs in the shop has reached to the maximum.

MSOP : Same as S/OPN.

MWB : This is a performance measure. The variance in the work of each machine over all time periods is calculated. Then an overall index is obtained by averaging over all machines. This has been used by Irastorza and Deane (1974).

NORR : All orders are released from the order release pool on arrival.

PBB : This is an order release rule used by Philipoom *et al.* (1993). Following is the description given by the authors. PBB mechanism first requires that a maximum load (which includes work being processed and waiting for processing) be set for all machines in the shop (which is PBB threshold). The procedure then involves a two step approach. In step one, the queue of jobs waiting for entry into the shop (pre-shop backlog) is sequenced in increasing order by each job's unique PBB slack ratio (S). A machine's slack is defined as the difference between the PBB threshold and work already committed to it in the form of jobs on the shop floor. The slack ratio attempts to identify the average proportion of slack of all the machines visited by a job that is consumed by that particular job. Then the job which consumes a smaller proportion of slack of machines in its path on an average would be a more desirable candidate for entry into the shop. The slack ratio also penalizes those jobs which have relatively large processing times at temporarily constrained machines. It is calculated as follows:

$$S_j = \frac{\sum_{i=1}^{m} \frac{P_{ij}}{T - L_i}}{N_j}$$

where, S_j = Slack ratio of job j,

P_{ij} = Processing time of job j at machine i,

		(P_{ij}=0 if machine i is not on job j's route),
T	=	Capacity threshold,
L_i	=	Current total load at machine i,
N_j	=	Number of operations required by job j, and
m	=	Number of machines in the shop.

Staring with the first job in the ordered queue, stage two begins by evaluating the job's unique path through the shop. If the current load at each machine along the job's path plus the job's processing time at the machine is below the PBB threshold, the job is released into the shop. This new release, if implemented, would increase the load on all the machines in the job's path. The current machine load not only includes the work in its queue, but also the work contained in all the jobs which are presently in the shop and are going to visit this machine centre in the future. The capacity load is evaluated for each operation as follows:

$$L_i + P_i \leq T \qquad \forall\, i \in I(j).$$

If any machine along the job's path has a load greater than the PBB threshold minus the job's processing time at that machine, the job is retained in the pre-shop backlog. The next job in the pre-shop file, as ordered by slack ratio, is considered for release. Using the same procedure, the ORR system continues to check all jobs in the pre-shop file.

QWB : The variance of queue size in work hours for each machine over time.

An overall index is obtained by averaging over all machines. This performance measure has been used by Irastorza and Deane (1974).

RAN : This order release rule releases orders at random time intervals.

S/OPN : This dispatching rule calculates the loading priority of a job in a queue on the basis of the minimum remaining slack per each of the remaining operations.

SPT : This dispatching rule calculates the loading priority of a job in a queue on the basis of the shortest total expected processing time.

SRPT : This dispatching rule calculates the loading priority of a job in a queue on the basis of the shortest expected remaining processing time.

SWB : This is a performance measure. This is the variance of the utilization of the shop as a whole taken ver time. This has been used by Irastorza and Deane (1974).

WCEDD : WCEDD is an order release rule, used by Melnyk and Ragatz (1989). According to this, the release is initiated whenever the work in the queue at any work centre drops below a minimum level. The pool selection rule selects the job with the earliest due date among those jobs with their first operation at the work centre which triggered the release. The WCEDD approach combines a shop-based triggering mechanism with a local selection rule.

Appendix B

Input File Description

The purpose of this appendix is to provide the detailed description of the input file called *JobInfoFile*. A generic format of this file and the file listing are given in this appendix.

B.1 Format of *JobInfoFile*

<number of order types>

<# of operations in the 1st order type> <cumulative probability of arrival of 1st order type>
<1st machine number for 1st order type> <mean process time at this machine>
<2nd machine number for 1st order type> <mean process time at this machine>

. .
. .
. .

<Final machine number for 1st order type> <mean process time at this machine>

<# operations for order type *i*> <cumulative probability of arrival of *i*th order type>
<machine for 1st operation for this order type> <mean operation time>

. .
. .
. .

<machine for last operation for the order type> <mean operation type>

. .
. .
. .

<number of steps in the last order type> <cumulative prob. of arrival of last order type>
<1st machine number for last order type> <mean process time at this machine>
<2nd machine number for last order type> <mean process time at this machine>

. .
. .
. .

<Final machine number for last order type> <mean process time at this machine>

Figure B.1: Generic Format of *JobInfoFile*

B.2 JobInfoFile Listing

The contents of the *JobInfoFile* were not changed during the research reported in this thesis. The file contents are listed below in multi-column format to save space.

```
143

4 0.00699
1   2.5
3   3.5
6   2.5
8   3.5

4 0.01399
1   2.5
3   3.5
6   2.5
9   3.5

4 0.02098
1   2.5
3   3.5
6   2.5
10   3.5

3 0.02797
1   2.5
3   3.5
6   2.5

4 0.03497
1   2.5
3   3.5
7   2.5
8   3.5

4 0.04196
1   2.5
3   3.5
7   2.5
9   3.5

4 0.04895
1   2.5
3   3.5
7   2.5
10   3.5

3 0.05594
1   2.5
3   3.5
7   2.5

3 0.06294
1   2.5
3   3.5
8   3.5

3 0.06993
1   2.5
3   3.5
9   3.5

3 0.07692
1   2.5
3   3.5
10   3.5

2 0.08392
1   2.5
3   3.5

4 0.09091
1   2.5
4   3.5
6   2.5
8   3.5

4 0.09790
1   2.5
4   3.5
6   2.5
9   3.5

4 0.10490
1   2.5
4   3.5
6   2.5
10   3.5

3 0.11189
1   2.5
4   3.5
6   2.5

4 0.11888
1   2.5
4   3.5
7   2.5
8   3.5

4 0.12587
1   2.5
4   3.5
7   2.5
9   3.5

4 0.13287
1   2.5
4   3.5
7   2.5
10   3.5

3 0.13986
1   2.5
4   3.5
7   2.5

3 0.14685
1   2.5
4   3.5
8   3.5

3 0.15385
1   2.5
4   3.5
9   3.5

3 0.16084
1   2.5
4   3.5
10   3.5

2 0.16783
1   2.5
4   3.5

4 0.17483
1   2.5
5   3.5
6   2.5
8   3.5

4 0.18182
1   2.5
5   3.5
6   2.5
9   3.5

4 0.18881
1   2.5
5   3.5
6   2.5
10   3.5

3 0.19580
1   2.5
5   3.5
6   2.5

4 0.20280
1   2.5
5   3.5
7   2.5
8   3.5

4 0.20979
1   2.5
5   3.5
7   2.5
9   3.5

4 0.21678
1   2.5
5   3.5
7   2.5
10   3.5

3 0.22378
1   2.5
5   3.5
7   2.5

3 0.23077
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5   3.5
8   3.5

3 0.23776
1   2.5
5   3.5
9   3.5

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10   3.5

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6   2.5
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9   3.5

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1   2.5

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6   2.5
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7   2.5
9   3.5

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7   2.5
10   3.5

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7   2.5

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3   3.5
9   3.5

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3   3.5

4 0.42657
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6   2.5
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6   2.5
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7   2.5
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```

```
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7    2.5
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10    3.5

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4 0.51049
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8    3.5

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6    2.5
9    3.5

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7    2.5
10    3.5

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9    3.5

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2    2.5
5    3.5

3 0.59441
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6    2.5
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9    3.5

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6    2.5
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8    3.5

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9    3.5

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6    2.5
10    3.5

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6    2.5

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3    3.5
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8    3.5

3 0.71329
3    3.5
7    2.5
9    3.5

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3    3.5
7    2.5
10    3.5

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9    3.5

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6    2.5
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6    2.5

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8    3.5

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9    3.5

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10    3.5

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9    3.5

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10    3.5

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9    3.5

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10    3.5

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10    3.5

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8    3.5

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9    3.5

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10    3.5

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2 0.95804
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8    3.5

2 0.96503
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9    3.5

2 0.97203
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10    3.5

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1 0.98601
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1 0.99301
9    3.5

1 1.00000
10    3.5
```

Appendix C

Strategic Accept/Reject Decisions

This appendix schematically depicts the hierarchy of different strategic accept/reject decisions.

The following diagram depicts different strategic possibilities regarding the accept/reject decision of a customer order. However, this diagram is not exhaustive in nature.

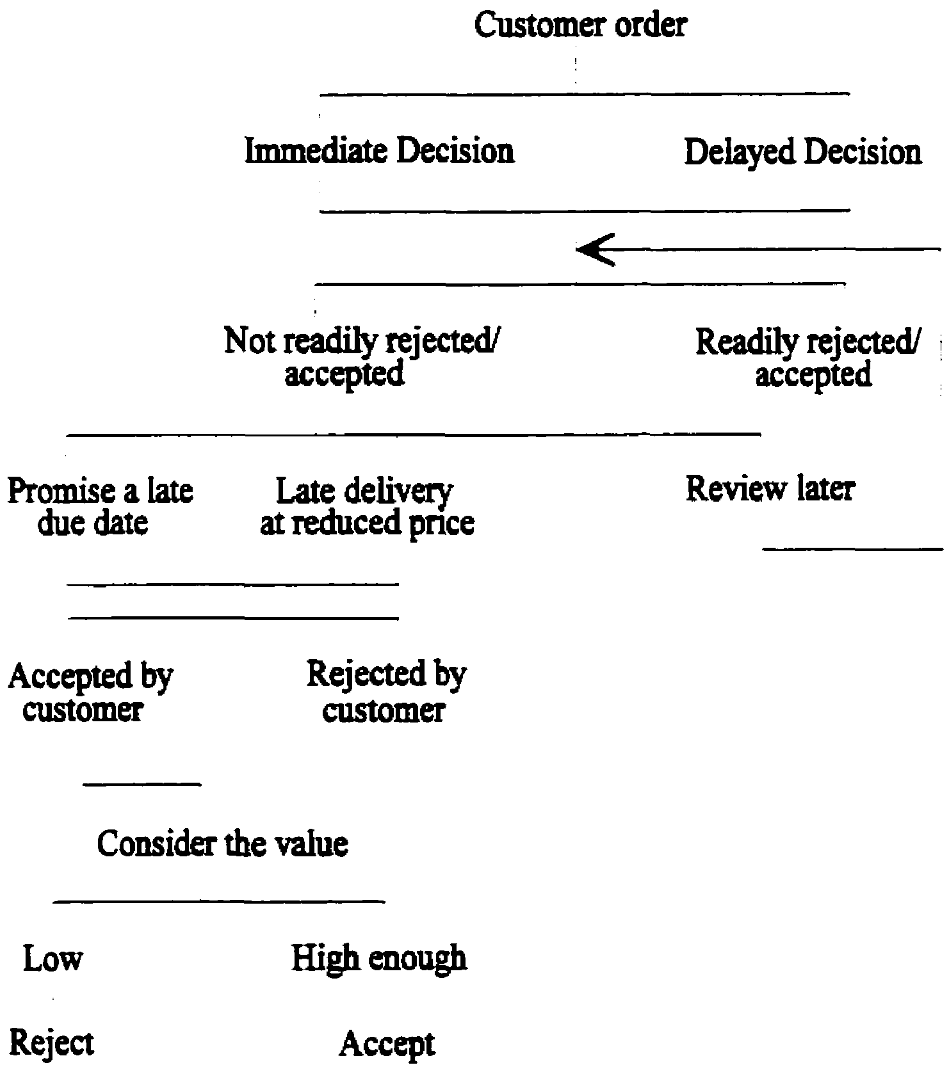

Figure C.1: Strategic Accept/Reject Decisions

Appendix D

Glossary of Acronyms and Special Terms

This appendix provides a categorized list of acronyms and special terms used in this thesis. The acronyms used in the context of literature review were provided in Appendix A. So they are not duplicated here.

D.1 Acronyms Concerning Performance Measures

OFT	:	Overall Flow Time
OMLT	:	Overall Manufacturing Lead Time
OPA	:	Overall Percent Achievement
OPRL	:	Overall Percent Rejection Loss
OPTL	:	Overall Percent Tardy Loss
OWTORP	:	Overall Waiting Time in the Order Release Pool
RPA	:	Regular Percent Achievement
RPRL	:	Regular Percent Rejection Loss
RPTL	:	Regular Percent Tardy Loss
R*x*PA	:	Regular *x*-step Percent Achievement (x = 1, 2 , 3, 4)
R*x*PRL	:	Regular *x*-step Percent Rejection Loss (x = 1, 2 , 3, 4)
R*x*PTL	:	Regular *x*-step Percent Tardy Loss (x = 1, 2, 3, 4)
UPA	:	Urgent Percent Achievement
UPRL	:	Urgent Percent Rejection Loss
UPTL	:	Urgent Percent Tardy Loss
U*x*PA	:	Urgent *x*-step Percent Achievement (x = 1, 2 , 3, 4)
U*x*PRL	:	Urgent *x*-step Percent Rejection Loss (x = 1, 2 , 3, 4)
U*x*PTL	:	Urgent *x*-step Percent Tardy Loss (x = 1, 2, 3, 4)
*x*PA	:	*x*-step Percent Achievement (x = 1, 2 , 3, 4)
*x*PRL	:	*x*-step Percent Rejection Loss (x = 1, 2 , 3, 4)
*x*PTL	:	*x*-step Percent Tardy Loss (x = 1, 2, 3, 4)

D.2 Acronyms Concerning Experimental Factors and Parameters

AR	:	Accept/Reject rule options
CL	:	Control Limit (generic representation) for an OR rule

CL_BUSM	:	CL for the BUSM OR rule
CL_TRL	:	CL for the TRL OR rule
DDT	:	Due Date Tightness
DL	:	Demand Level
DLV	:	Demand Level Variability
DR	:	Dispatching Rule options
HL	:	Urgent Limit (generic representation) for an AR rule
HL_BUS	:	Urgent Limit for the BUS AR rule
HL_TAL	:	Urgent Limit for the TAL AR rule
Kincr	:	The control parameter used in the SIMUL AR rule
Kr	:	A proportionality constant used in calculation of the revenue of a regular order
Ktr	:	A proportionality constant used in the tardiness cost calculation of a regular order
Ktu	:	Similar to Ktr but used in the case of an urgent order
Ku	:	Similar to Kr but used in the case of an urgent order
OR	:	Order Release Options
PTV	:	Process Time Variability
PUO	:	Percent of Urgent Orders
RegFTA	:	Constant flow time allowance for a regular order
RL	:	Regular Limit (generic representation) for an AR rule
RL_BUS	:	Regular Limit for the BUS AR rule
RL_TAL	:	Regular Limit for the TAL AR rule
UrgFTA	:	Constant flow time allowance for an urgent order

D.3 Acronyms Concerning Cost Related Terms

DC	:	Due-date deviation Cost
EC	:	Earliness Cost
HC	:	Holding Cost
LC	:	Lead-time Cost
OH	:	Fixed Overhead cost
PFT	:	Profit
Rev	:	Revenue
TC	:	Tardiness Cost
VC	:	Variable production Cost

D.4 Acronyms Concerning Accept/Reject Rules

BUS	:	Accept/reject rule based on the accepted load on the busiest machine on the order's route
FA	:	Full Acceptance
SIMUL	:	Accept/reject rule based on simulation
TAL	:	Accept/reject rule based on the total accepted load in the system

D.5 Acronyms Concerning Order Release Rules

BUSM	:	Order release rule based on the released load on the busiest machine on the order's route
IMM	:	Immediate release
TRL	:	Order release rule based on the total released load on the shop floor

D.6 Acronyms Concerning Dispatching Rules

EDT	:	Earliest Due Time
FSFS	:	First in System First Served
S/OPN	:	Slack per Operation

D.7 Miscellaneous Acronyms and Terms

AT	:	Arrival Time of an order into the system
DT	:	Due Time of an order
IAT	:	Inter Arrival Time
CoV	:	Coefficient of Variation
JIT	:	Just In Time
MTO	:	Make-To-Order
MTS	:	Make-To-Stock
ORP	:	Order Release Pool
ORR	:	Order Review and Release
T_c	:	Critical tardiness
TWK	:	Total estimated work content of an order
WIP	:	Work In Progress
WLC	:	Workload Control

Appendix E

Description of the Simulation Model

This appendix provides a detailed description of the simulation model. The section E.1 contains the description of the main model while different important features of the model have been discussed in the section E.2.

E.1 Detailed Description of the Main Model

E.1.1 *Phd.mod* File

The main logic of the model is defined in the file *Phd.mod* which is divided into six primary code segments.

The *first segment* of the logic is devoted to defining miscellaneous control variables depending on the corresponding experimental factor levels (which are declared in the experiment file). The logic in this segment also reads the shop data from the input file called *JobInfoFile*. *JobInfoFile* contains the routing information of all possible job types. In the beginning of this segment, a single entity is created which causes the files to be read before it is disposed of.

The *second segment* of the model deals with the actual creation of the candidate orders for the manufacturing system. Order creation includes the definition of all order attributes such as job type, priority, due date, total number of steps, and potential revenue. After these assignments, the entity representing the order is sent to the *Phd_AR.mod* file so that the decision as to whether or not the order will be accepted or rejected can be done.

In the *third segment* of the model, the entity returns back from *Phd_AR.mod* file with the decision of acceptance or rejection. If the order is to be rejected, the entity is sent to the logic dealing with rejection (or, false acceptance which pretends the order to be accepted in the first of the two pilot sessions of the simulation-based accept/reject rule). Two quantities are recomputed here which are maximum possible revenue (*MaxPossRevenue*) and loss due to the rejection of an order (*RejectLoss*). Information on each of these two quantities is collected on an overall basis, by order class, by number of steps involved in the order, and by each of x-class y-step orders (where $x = 1, 2, 3$ or, 4 and y = urgent or regular). Also the counter for number of rejected orders is updated. After this the entity is disposed of since it is no longer of any interest. If the order is accepted (or, even falsely accepted), it is duplicated ans the original is sent to the order release pool which is basically a detached queue, while the duplicated entity is sent to re-rank the order release pool and to check for the possibility of an order release. Before duplicating and sending the original entity to the order release pool, a number of variables, counters and tallies are updated.

The *fourth main model segment* defines what happens when a job is released from the order release pool. After releasing the order from the order release pool, the entity representing the order updates different tallies, status variables and attributes. Before the entity is finally routed to the destination machine (according to its process plan), it checks for another release if the order release pool is not empty and the machine at the first step of the order is busy. It is checked if the machine at the first step is busy or not, because in the case of a busy machine, the order sits in the queue and there is not any possibility of another checking immediately after the release. But if the machine is idle, the order seizes the machine straight away and another order checking is possible without delay. Also re-ranking of the order release pool is not necessary in this case, because there is no time delay possible between this checking and the previous release. So the sequence of the order release pool may not alter.

The *fifth main model segment* defines a generic station representing the behavior of each of the ten machines in the system. If the machine is busy when a job arrives the job waits in a detached queue which represents the queue in front of the machine. Otherwise, the job is directly sent to seize the machine. Just before seizing the machine, different tallies for queue times and, after seizing the machine many status variables and attributes are updated, while just after seizing the machine the entity is duplicated and sent to re-rank the order release pool before checking for an order release. The original entity is delayed for the stipulated period of time after which the machine is released. On releasing the machine, the same set of status variables and attributes are updated as was done before seizing the machine. At this point, the order release pool is re-ranked and the possibility of a release of an order is checked again in the same fashion as before and the original entity is routed to its next machine (which is at the top of the fifth segment) unless it is complete. If it is complete, it goes to the final segment of the model.

The *sixth segment* of the model deals with statistics collection for completed jobs prior to exit from the system. Specific statistics are collected depending on whether the order is tardy or early. Maximum possible revenue, actual total revenue and tardy loss are recomputed. Different tallies such as flow time, manufacturing lead time (MLT), and lateness are updated and the counts of finished jobs are incremented. Normal jobs are simply disposed of at this point, while things are handled differently for the special simulation based pilot runs. If the control is in a pilot run and the exiting job makes the system empty of work, then a special "end of pilot simulation session" action is initiated. Near the end of this sixth segment, there is a small segment which is required to safely terminate a simulation with the simulation based accept/reject rule, since we must avoid accidental termination during a simulation based test run. At the very end there is another small segment to cause a number of global variables (meant for statistics collection) to be cleared after the warm up period is over. This is necessary because these global variables occur together with different COUNTER variables in many of the expressions of the OUTPUTS elements. These COUNTER variables get cleared at the end of the warm up period automatically, but the same is not true for the global variables.

E.1.2 *Phd_AR.mod* File

The logic in the *Phd_AR.mod* file involves different alternative accept/reject rules. The logic of these rules is quite straightforward except the one pertaining to the simulation based accept/reject rule which will be described in the next section in detail.

E.1.3 *Phd_OR.mod* File

Phd_OR.mod contains the logic for the different order release rules. The order release pool (ORP) is basically a detached queue, having a ranking rule as LVF[slack per operation]. When an entity is sent to the ORP, it is placed in the ORP according to its value of slack per operation. If two such entities have the same slack per operation, then they are automatically placed according to LVF[time of entry into the ORP] which is equivalent to LVF [time of entry into the system], because all the entities enter the ORP just after entering into the system. So virtually there is no difference between the time of entry into the system and that into the ORP. A SEARCH block searches for the entity which satisfies the search condition (*i.e.* the release condition). This search activity goes on until such an entity is found (*i.e.* the condition is satisfied) or the end of the queue is reached. If the condition is satisfied, the searching entity is sent to a REMOVE block to remove the particular entity from the ORP. Philosophically the release should be possible at any time. But the release condition might change only at four different times *viz.*

(i) just before sending an order to the ORP,
(ii) just after release of an order from the ORP,
(iii) just after seizing a machine and,
(iv) just after release of a machine.

So, it is sufficient to check the possibility of a release at these four points only. If two orders have the same slack per operation and if both are eligible to be released, then the tie is broken on the basis of earlier entry into the system, *i.e.* whichever is closer to the head of the ORP will be released first. The logic to the specific order release rules are not described here as they are quite straightforward.

E.1.4 *Phd_DR.mod* File

The logic for dispatching rules resides in the file *Phd_DR.mod*. This logic is quite simple and self-evident. So it is not described here.

E.2 Important Features of the Model

E.2.1 Accept/Reject Decision Through Forward Simulation

The basic mechanism of simulation based accept/reject rule has been already described conceptually in the section 3.2.2 (d). In this section, the modeling aspect of the same will be addressed.

Every time, a new order arrives in, the original entity is detained in a queue in front of a WAIT block, while its duplicate is sent to execute the event #1 which saves the status of the system in a file called *X.snp*. If this arriving entity is the first entity in this simulation run, then an event #201 is executed, which is responsible for copying the SIMAN generated data files to respective external files. But in other cases (*i.e.* if the arriving entity is not the first entity), the event #200 is executed which is responsible for cutting the headers of all the SIMAN generated data files and append the rest of the data file to the respective external files. After this is done, the variable *DummySession* is assigned a value of unity, which indicates that the control is in the first pilot session. The variable *FalseAccept* is assigned a value of unity, which indicates that when this duplicated entity will go to the *third main model segment*, it will be falsely accepted and will continue through the model. Each and every job that has been finished processing, will check before exit if the system is empty. If not, the system will keep on processing the existing jobs in the system since no new arrivals are occurring during this session. On the other hand, if the system is empty, the value of the variable *OverallProfitInDummySession(1)* is recorded and the value of *DummySession* is changed to a value of 2 indicating that the second pilot simulation will start. At this point, the event #2 is executed which retrieves the status of the shop from the file *X.snp*. While restoring the old status, the current values of the several global variables *viz. DummySession, FirstTimeSave* and *OverallProfitInDummySession* are retained. The retention of the values of the variables is done through the user code in C. Before we restore any previous status, we store the current values of those special variables in *local variables*. Then we restore the previous status. After restoration, we reassign those special variables by their unchanged values as stored in the local variables and then we bring those reassigned variables back into SIMAN model through usual procedure. Thus in effect, we are able to restore the old status of the system while retaining the current values of those variables. In the beginning of the second pilot session, an initial check is done if the system is already empty. If it is so, the value of *OverallProfitInDummySession(2)* is recorded and event #2 is executed which restores the status from the file *X.snp*, without overwriting the current value of the variable *OverallProfitInDummySession(2)*. However, if at the beginning of the pilot session 2, the system is not empty, the active entity which is performing this check is disposed from the model and the model is let run, until the system becomes empty by itself. In either case, the status from the file *X.snp* is restored and a signal is sent to the original entity waiting in the *WaitQ*, causing it to be released from the *WaitQ*. Now this original entity will compare the values of the variables *OverallProfitInDummySession(1)* and *OverallProfitInDummySession(2)* and will take the necessary decision accordingly and *DummySession* will change to zero again. After this, the control will go to the *third main model segment* of the file *Phd.mod*. The model will continue in this real mode until another new order enters into the system. In this way, the model runs until the simulation time reaches *ReplicationLength*, when an entity is created to terminate the simulation run. Care is taken so that the run terminates in the real mode and not during any of the pilot simulation runs. After the simulation run is over, all the SIMAN generated data files (which contain the header and also the footer) are cut of their headers and appended to the respective external files. These external files, having both the SIMAN header and footer, are possible to be processed by the ARENA output analyzer.

E.2.2 Automatic Saving and Restoration of the Status

During the execution of this simulation, it is needed to save and restore snapshot files multiple number of times and also it is to be done on a conditional basis, the condition being based on the information of the status of the system. So in the case of a large, number of events of save and restoration, it is virtually impossible to save and restore the snapshots manually through the help of interactive run controller of SIMAN. So it is needed to use some technique, where it is possible to save and restore the snapshots in an unattended mode.

To remedy this problem, a special internal function has been used and the save/restore has been done just by calling that function in the user code. The function is as follows:

*void srDbg_ReadWriteSnapshot (char *filename, SMINT iop);*

where, the <filename> variable should be a character string containing the filename and <*iop*> variable should take a value of 8 for SAVE, and a value of 9 for RESTORE.

E.2.3 Prevention Against Losing the Data in the Output File While Restoring a Previous Snapshot

Whenever a snapshot is restored, the simulation starts with a new set of Tally and Dstat registers. So all the data points that were already in the registers are lost. In the present experiment, it is important to prevent the data points (those which are collected in the real mode only *i.e.* when *DummySession* is zero) from being lost. Hence, just before leaving the real mode (after which the file *X.snp* will be restored through event #2), all the data points from the default registers (*.dat*) is copied into an external file (*.ext*). If this is for the first time, the content of the "*.dat*" files are copied into the "*.ext*" files as it is; but in other cases, the header of the "*.dat*" files are eliminated first and then the rest of the contents are appended to the "*.ext*" files.

A similar situation arises when orders are accepted or rejected through forward simulation. In this case, every time, the virtual simulation run ends, the snapshot from the file X3.snp is restored. Before this restoration, the content of all the *.dat* files are appended to the .ext files, after cutting the header portion of the *.dat* files. However this is done only in the emulation mode; but not in the scheduler mode; because, it is not intended to accept the values other than in the emulation mode.

In this way, after multiple restoration of old snapshots, the whole set of useful data rests in the *.ext* files; but not in the *.dat* files. When the simulation terminates, cutting the header and appending the contents of the *.dat* files to the *.ext* files is done once more for the last time. This causes the *.ext* file to contain the last set of data points together with the footer of the *.dat* files. This footer is created only when the simulation terminates. So this resulting *.ext* files contain the header, the whole set of data points corresponding to the emulation mode and the footer. Moreover, these *.ext* files can be added to the data group of ARENA's output processor.

E.2.4 Re-ranking of the Order Release Pool *Releasepool*

Re-ranking of the order release pool is necessary every time the possibility of an order release is checked, except in one occasion (when the checking is done by a just released order with the fact that the machine in the first step of the released order is busy). The reason of not re-ranking the pool in this case is that there is no time delay possible between the previous release and this present checking. So no change in the values of slack per operation of the orders waiting in the order release pool is possible and hence no change in their relative ranking in the pool. The mechanism of re-ranking the pool is as follow.

To re-rank the pool, all the entities from the *ReleasePool* are removed, to insert them into the *TempReleasePool* one by one until the *ReleasePool* is empty and then we remove the entities from the *TempReleasePool*, to insert them back into the *ReleasePool* one at a time, until the *TempReleasePool* is empty. The *ReleasePool* has a ranking rule which is LVF [slack per operation], so that the entities are placed in the *ReleasePool* accordingly. In the associated logic, two very small delays called *microdelay* (each equal to 10^{-20} minutes), have been introduced. This small delay helps to schedule the order of activities in the event calendar properly as described above, but they do not induce any delay in the system which is practically significant.

Appendix F

Results for Preliminary Experiments

This appendix contains the results for the preliminary experiments of Chapter 4 involving two classes of order. They are displayed in **Table F.1** and **Table F.2**.

Table F.1: Results for Different Variants of Percent Achievements

	DL			DLV			PTV		
	0.75	**0.85**	**0.95**	**0.10**	**0.55**	**1.00**	**0.10**	**0.30**	
OPA	99.107	90.183	-3.368	90.183	86.773	79.511	90.183	85.445	
RPA	99.104	89.919	-8.687	89.919	86.363	78.751	89.919	85.017	
UPA	99.147	94.201	77.454	94.201	92.991	91.057	94.201	91.944	
R1PA	98.573	76.084	-904.992	76.084	64.686	39.960	76.084	60.882	
R2PA	98.591	78.708	-196.556	78.708	69.778	49.911	78.708	67.473	
R3PA	99.146	91.379	51.054	91.379	88.733	82.847	91.379	87.580	
R4PA	99.365	95.065	81.042	95.065	93.789	91.795	95.065	92.894	
U1PA	97.691	82.829	-79.144	82.829	79.346	65.512	82.829	78.219	
U2PA	99.357	94.891	80.692	94.891	93.979	92.132	94.891	93.345	
U3PA	99.380	95.319	83.736	95.319	94.303	92.594	95.319	93.255	
U4PA	98.838	93.233	79.618	93.233	91.780	90.445	93.233	90.521	
	PUO			**RegFTA**			**UrgFTA**		
	0.05	**0.15**	**0.25**	**25**	**30**	**35**	**10**	**15**	**20**
OPA	90.183	88.564	86.813	84.034	90.183	94.136	87.259	89.050	90.183
RPA	89.919	87.533	84.629	83.563	89.919	94.005	89.010	89.024	89.919
UPA	94.201	93.292	92.057	91.191	94.201	96.129	60.652	89.452	94.201
R1PA	76.084	71.729	66.889	58.450	76.084	85.827	72.809	73.381	76.084
R2PA	78.708	73.905	68.968	64.893	78.708	87.476	76.591	76.334	78.708
R3PA	91.379	89.169	86.242	86.180	91.379	94.883	90.759	90.875	91.379
R4PA	95.065	93.827	92.188	92.045	95.065	96.974	94.604	94.593	95.065
U1PA	82.829	82.055	76.135	54.119	82.829	92.184	96.130	89.946	82.829
U2PA	94.891	93.912	92.598	88.273	94.891	97.367	89.636	94.772	94.891
U3PA	95.319	94.177	93.122	93.908	95.319	96.718	68.516	91.928	95.319
U4PA	93.233	92.629	91.552	92.025	93.233	94.994	32.068	83.312	93.233

Table F.2: Results for Different Variants of Flow Times

	DL			DLV			PTV	
(mean)	**0.75**	**0.85**	**0.95**	**0.10**	**0.55**	**1.00**	**0.10**	**0.30**
OFT	17.811	26.768	76.453	26.768	28.499	32.156	26.768	29.266
RFT	18.039	27.249	79.153	27.249	29.043	32.844	27.249	29.832
UFT	13.508	17.649	25.377	17.649	18.196	19.126	17.649	18.551
R1FT	10.492	21.771	294.380	21.771	25.426	33.495	21.771	26.583
R2FT	16.268	28.427	118.280	28.427	31.535	38.615	28.427	32.474
R3FT	18.982	27.324	44.516	27.324	28.610	31.192	27.324	29.272
R4FT	20.441	27.425	35.576	27.425	28.180	29.391	27.425	28.917
U1FT	8.101	14.060	51.613	14.060	14.951	19.155	14.060	15.969
U2FT	11.559	16.206	23.189	16.206	16.901	17.741	16.206	16.930
U3FT	13.699	17.818	22.981	17.818	18.273	19.007	17.818	18.723
U4FT	16.887	19.926	24.031	19.926	20.373	20.781	19.926	20.714
(CoV)								
OFT	0.438	0.629	2.306	0.629	0.719	0.871	0.629	0.772
RFT	0.436	0.627	2.280	0.627	0.717	0.868	0.627	0.770
UFT	0.351	0.396	0.877	0.396	0.397	0.436	0.396	0.413
R1FT	1.002	1.668	1.964	1.668	1.799	1.997	1.668	1.978
R2FT	0.556	0.826	1.077	0.826	0.924	1.018	0.826	0.983
R3FT	0.353	0.368	0.391	0.368	0.385	0.416	0.368	0.389
R4FT	0.265	0.237	0.098	0.237	0.239	0.234	0.237	0.232
U1FT	1.021	1.340	1.486	1.340	1.325	1.302	1.340	1.325
U2FT	0.390	0.374	0.244	0.374	0.367	0.365	0.374	0.388
U3FT	0.238	0.248	0.117	0.248	0.251	0.245	0.248	0.253
U4FT	0.162	0.169	0.091	0.169	0.170	0.171	0.169	0.182

Table F.2 (contd.): Results for Different Variants of Flow Times

	PUO			RegFTA			UrgFTA		
(mean)	**0.05**	**0.15**	**0.25**	**25**	**30**	**35**	**10**	**15**	**20**
OFT	26.768	26.862	26.908	26.858	26.768	26.824	26.944	27.014	26.768
RFT	27.249	28.405	29.683	27.220	27.249	27.401	27.694	27.668	27.249
UFT	17.649	18.081	18.600	19.987	17.649	15.891	12.730	14.602	17.649
R1FT	21.771	23.161	24.639	25.395	21.771	20.339	22.847	22.584	21.771
R2FT	28.427	30.064	31.763	30.377	28.427	27.354	29.062	29.137	28.427
R3FT	27.324	28.330	29.562	26.453	27.324	27.933	27.626	27.587	27.324
R4FT	27.425	28.273	29.135	25.718	27.425	28.537	27.733	27.694	27.425
U1FT	14.060	14.298	15.587	21.818	14.060	11.390	6.536	10.179	14.060
U2FT	16.206	16.725	17.159	19.302	16.206	13.973	10.013	12.632	16.206
U3FT	17.818	18.381	18.862	19.487	17.818	16.114	13.082	14.944	17.818
U4FT	19.926	20.172	20.558	21.035	19.926	18.844	16.793	17.378	19.926
(CoV)									
OFT	0.629	0.677	0.720	0.766	0.629	0.564	0.680	0.677	0.629
RFT	0.627	0.672	0.714	0.767	0.627	0.557	0.668	0.669	0.627
UFT	0.396	0.393	0.423	0.573	0.396	0.350	0.293	0.289	0.396
R1FT	1.668	1.727	1.747	1.916	1.668	1.416	1.781	1.773	1.668
R2FT	0.826	0.893	0.956	0.953	0.826	0.750	0.874	0.883	0.826
R3FT	0.368	0.391	0.418	0.376	0.368	0.373	0.373	0.374	0.368
R4FT	0.237	0.236	0.240	0.192	0.237	0.278	0.237	0.238	0.237
U1FT	1.340	1.323	1.444	1.692	1.340	0.957	0.500	0.786	1.340
U2FT	0.374	0.384	0.402	0.482	0.374	0.382	0.240	0.315	0.374
U3FT	0.248	0.247	0.246	0.218	0.248	0.269	0.155	0.197	0.248
U4FT	0.169	0.165	0.163	0.153	0.169	0.172	0.129	0.120	0.169

Appendix G

D-optimal Design

This appendix provides a brief description of the D-optimal design in section G.1. Section G.2 contains the justification for the selection of different terms in the regression equation from a generic cubic polynomial in 7 variables. Section G.3 shows a sample SAS program which produces a D-optimal design from an input candidate data set.

G.1 A Brief Introduction to D-optimal Design

John and Draper (1975) reviewed the regression designs through D-optimality. Among other literature dealing with D-optimal design, Mitchell (1974a, b), Meyer and Nachtsheim (1995) discussed different algorithms for D-optimal design while DuMouchel and Jones (1994) modified D-optimal design to reduce the bias caused from the assumed model.

Following is a brief description of the underlying theory of D-optimal design as given by John and Smith (1975).

The linear model

$$y_i = \mathbf{f}'(\mathbf{x}_i)\boldsymbol{\beta} + \epsilon_i\,, \qquad \text{where } i = 1, 2, 3, \ldots, n \tag{G.1}$$

can be expressed in matrix notation as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{G.2}$$

The vector $\mathbf{y}$ is an $n \times 1$ vector of observations; $\mathbf{X}$ is an $n \times p$ matrix, with row i containing $\mathbf{f}'(\mathbf{x}_i)$; $\mathbf{x}_i$ is a $q \times 1$ vector of predictor variables; $\mathbf{f}'(\mathbf{x}_i)$ is a $p \times 1$ vector which depends on the form of the response function assumed; $\boldsymbol{\beta}$ is a $p \times 1$ vector of unknown parameters; $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently and identically distributed random variables, with mean zero and variance σ^2. The experimental region is denoted by χ, and it is assumed that χ is compact and that $f_i(\mathbf{x}_i)$'s are continuous on χ.

It is also assumed that least square estimates of the parameters $\boldsymbol{\beta}$ are to be obtained. These are given by

$$\boldsymbol{\beta}_{est} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}, \tag{G.3}$$

and the variance-covariance matrix of $\boldsymbol{\beta}_{est}$ is

$$\mathbf{V}(\boldsymbol{\beta}_{est}) = \sigma^2(\mathbf{X}'\mathbf{X})^{-1}. \tag{G.4}$$

Then at point $\mathbf{x} \in \chi$, the predicted response is

$$y_{est}(\mathbf{x}) = \mathbf{f}'(\mathbf{x})\boldsymbol{\beta}_{est}, \tag{G.5}$$

with variance

$$v(y_{est}(\mathbf{x})) = \sigma^2\,\mathbf{f}'(\mathbf{x})(\mathbf{X}'\mathbf{X})^{-1}\mathbf{f}(\mathbf{x}). \tag{G.6}$$

The design problem consists of selecting vectors $\mathbf{x}_i$, $i = 1, 2, \ldots, n$ from χ such that the design defined by these n vectors is, in some defined sense, optimal. By and large, solutions to this problem consist of developing some sensible criterion based on the model (G.2), and using it to obtain optimal designs. An optimality criterion is a single number that summarizes how good a design is, and it is maximized or minimized by an optimal design.

D-optimality is related to the matrix $\mathbf{X}'\mathbf{X}$, known as *information matrix*. This matrix is important because it is proportional to the inverse of the variance-covariance matrix for the least squares estimates of the linear parameters of the model. A good design should minimize $(\mathbf{X}'\mathbf{X})^{-1}$, which is the same as maximizing the information $\mathbf{X}'\mathbf{X}$. D-optimality is based on the determinant of the information matrix for the design, which is the same as the reciprocal of the determinant of the variance-covariance matrix for the least squares estimates of the linear parameters of the model.

$$|\mathbf{X}'\mathbf{X}| = 1/\,|(\mathbf{X}'\mathbf{X})^{-1}|$$

The determinant is thus a general measure of the size of $(\mathbf{X}'\mathbf{X})^{-1}$.

G.2 Justification of the Effects Chosen in a Regression Model

A polynomial (cubic) regression equation in n variables has been fit for the observations of OPA obtained from the experiments suggested by the corresponding D-optimal design, where n is the number of factors varied in an experiment. However, it is to be noted that it is not possible to fit a generic cubic equation with the number of levels of the factors involved in the experiments in this research, since any effect containing a p^{th} power of a factor will need to have at least $(p+1)$ levels for that factor to estimate that effect. So for example, from an experiment it is not possible to estimate an effect containing DDT^2 or DL^3 since DDT has only 2 levels and DL has only 3.

G.3 An Example SAS Program to Generate D-optimal Experimental Design to Build Regression Model for the BUS-BUSM Scenario

```
proc optex data=WORK.CANBBD coding=orth;
class DR;
model HL_BUS RL_BUS CL_BUSM DR
      HL_BUS*HL_BUS RL_BUS*RL_BUS CL_BUSM*CL_BUSM DR*DR
      HL_BUS*RL_BUS HL_BUS*CL_BUSM HL_BUS*DR
      RL_BUS*CL_BUSM RL_BUS*DR
      CL_BUSM*DR
      HL_BUS*HL_BUS*HL_BUS RL_BUS*RL_BUS*RL_BUS CL_BUSM*CL_BUSM*CL_BUSM
      HL_BUS*HL_BUS*RL_BUS HL_BUS*HL_BUS*CL_BUSM HL_BUS*HL_BUS*DR
      RL_BUS*RL_BUS*HL_BUS RL_BUS*RL_BUS*CL_BUSM RL_BUS*RL_BUS*DR
      CL_BUSM*CL_BUSM*HL_BUS CL_BUSM*CL_BUSM*RL_BUS CL_BUSM*CL_BUSM*DR
      HL_BUS*RL_BUS*CL_BUSM HL_BUS*RL_BUS*DR HL_BUS*CL_BUSM*DR
      RL_BUS*CL_BUSM*DR;
generate iter=20;
output out=BBD_DES;
run;
quit;
```

Appendix H

Results from Two-stage Input Control

This appendix contains the results of the experiments involving two-stage input control contained in Chapter 4.

Table H.1: Expected OPA at Different Combinations of Control Limits in BUS-BUSM Scenario

HL_BUS	RL_BUS	CL_BUSM	DR	OPA
10	10	10	EDD	75.40
10	10	15		75.42
10	10	20		75.49
10	10	25		75.57
10	10	30		75.61
10	20	10		87.69
10	20	15		88.03
10	20	20		88.34
10	20	25		88.56
10	20	30		88.66
10	30	10		89.57
10	30	15		90.29
10	30	20		90.89
10	30	25		91.32
10	30	30		91.52
20	10	10	EDD	75.17
20	10	15		75.29
20	10	20		75.41
20	10	25		75.48
20	10	30		75.45
20	20	10		88.38
20	20	15		88.87
20	20	20		89.27
20	20	25		89.53
20	20	30		89.60
20	30	10		90.22
20	30	15		91.13
20	30	20		91.87
20	30	25		92.37
20	30	30		92.59
30	10	10	EDD	75.90
30	10	15		76.11
30	10	20		76.28
30	10	25		76.33
30	10	30		76.23
30	20	10		89.43
30	20	15		90.06
30	20	20		90.55
30	20	25		90.84
30	20	30		90.88
30	30	10		90.62
30	30	15		91.72
30	30	20		92.59
30	30	25		93.16
30	30	30		93.39

HL_BUS	RL_BUS	CL_BUSM	DR	OPA
10	10	10	S/OPN	78.07
10	10	15		78.02
10	10	20		78.04
10	10	25		78.09
10	10	30		78.11
10	20	10		89.72
10	20	15		89.94
10	20	20		90.13
10	20	25		90.26
10	20	30		90.27
10	30	10		91.72
10	30	15		92.25
10	30	20		92.67
10	30	25		92.93
10	30	30		92.99
20	10	10	S/OPN	78.55
20	10	15		78.63
20	10	20		78.73
20	10	25		78.79
20	10	30		78.78
20	20	10		91.39
20	20	15		91.79
20	20	20		92.10
20	20	25		92.29
20	20	30		92.31
20	30	10		93.61
20	30	15		94.36
20	30	20		94.95
20	30	25		95.32
20	30	30		95.42
30	10	10	S/OPN	78.55
30	10	15		78.76
30	10	20		78.93
30	10	25		79.00
30	10	30		78.94
30	20	10		91.99
30	20	15		92.55
30	20	20		92.98
30	20	25		93.23
30	20	30		93.24
30	30	10		93.83
30	30	15		94.79
30	30	20		95.54
30	30	25		96.00
30	30	30		96.15

Table H.2: Expected OPA at Different Combinations of Control Limits in BUS-TRL Scenario

HL_BUS	RL_BUS	CL_TRL	DR	OPA	HL_BUS	RL_BUS	CL_TRL	DR	OPA
10	10	50	EDD	74.12	10	10	50	S/OPN	76.12
10	10	100		74.99	10	10	100		77.67
10	10	150		75.36	10	10	150		78.39
10	10	200		75.48	10	10	200		78.55
10	10	250		75.61	10	10	250		78.41
10	20	50		87.36	10	20	50		88.59
10	20	100		88.00	10	20	100		89.84
10	20	150		88.20	10	20	150		90.34
10	20	200		88.21	10	20	200		90.34
10	20	250		88.31	10	20	250		90.10
10	30	50		89.99	10	30	50		91.51
10	30	100		90.61	10	30	100		92.70
10	30	150		90.86	10	30	150		93.19
10	30	200		90.99	10	30	200		93.25
10	30	250		91.27	10	30	250		93.14
20	10	50	EDD	75.91	20	10	50	S/OPN	76.85
20	10	100		76.57	20	10	100		78.20
20	10	150		76.75	20	10	150		78.76
20	10	200		76.72	20	10	200		78.78
20	10	250		76.73	20	10	250		78.53
20	20	50		90.06	20	20	50		90.49
20	20	100		90.55	20	20	100		91.62
20	20	150		90.63	20	20	150		92.01
20	20	200		90.56	20	20	200		91.94
20	20	250		90.60	20	20	250		91.67
20	30	50		92.47	20	30	50		93.46
20	30	100		93.01	20	30	100		94.58
20	30	150		93.21	20	30	150		95.04
20	30	200		93.32	20	30	200		95.10
20	30	250		93.61	20	30	250		95.01
30	10	50	EDD	75.39	30	10	50	S/OPN	76.43
30	10	100		76.05	30	10	100		77.78
30	10	150		76.25	30	10	150		78.37
30	10	200		76.27	30	10	200		78.46
30	10	250		76.37	30	10	250		78.31
30	20	50		90.05	30	20	50		90.83
30	20	100		90.60	30	20	100		92.03
30	20	150		90.76	30	20	150		92.52
30	20	200		90.81	30	20	200		92.58
30	20	250		91.00	30	20	250		92.47
30	30	50		91.83	30	30	50		93.44
30	30	100		92.50	30	30	100		94.70
30	30	150		92.85	30	30	150		95.32
30	30	200		93.14	30	30	200		95.57
30	30	250		93.65	30	30	250		95.71

Table H.3: Expected OPA at Different Combinations of Control Limits in TAL-BUSM Scenario

HL_TAL	RL_TAL	CL_BUSM	DR	OPA	HL_TAL	RL_TAL	CL_BUSM	DR	OPA
50	50	10	EDD	70.56	50	50	10	S/OPN	70.77
50	50	15		71.25	50	50	15		71.94
50	50	20		71.75	50	50	20		72.61
50	50	25		71.99	50	50	25		72.73
50	50	30		71.88	50	50	30		72.20
50	150	10		88.57	50	150	10		89.58
50	150	15		89.76	50	150	15		91.21
50	150	20		90.64	50	150	20		92.24
50	150	25		91.15	50	150	25		92.59
50	150	30		91.19	50	150	30		92.19
50	250	10		85.95	50	250	10		88.47
50	250	15		87.60	50	250	15		90.53
50	250	20		88.84	50	250	20		91.89
50	250	25		89.58	50	250	25		92.45
50	250	30		89.75	50	250	30		92.15
150	50	10	EDD	72.39	150	50	10	S/OPN	71.05
150	50	15		72.81	150	50	15		71.94
150	50	20		73.14	150	50	20		72.44
150	50	25		73.30	150	50	25		72.47
150	50	30		73.21	150	50	30		71.97
150	150	10		89.79	150	150	10		89.89
150	150	15		90.88	150	150	15		91.42
150	150	20		91.77	150	150	20		92.45
150	150	25		92.38	150	150	25		92.91
150	150	30		92.63	150	150	30		92.71
150	250	10		84.48	150	250	10		86.73
150	250	15		86.22	150	250	15		88.88
150	250	20		87.64	150	250	20		90.41
150	250	25		88.67	150	250	25		91.26
150	250	30		89.22	150	250	30		91.34
250	50	10	EDD	71.38	250	50	10	S/OPN	72.34
250	50	15		71.71	250	50	15		73.14
250	50	20		72.06	250	50	20		73.65
250	50	25		72.33	250	50	25		73.80
250	50	30		72.46	250	50	30		73.50
250	150	10		86.61	250	150	10		89.64
250	150	15		87.80	250	150	15		91.27
250	150	20		88.88	250	150	20		92.50
250	150	25		89.79	250	150	25		93.24
250	150	30		90.43	250	150	30		93.43
250	250	10		77.04	250	250	10		82.87
250	250	15		79.06	250	250	15		85.30
250	250	20		80.86	250	250	20		87.21
250	250	25		82.36	250	250	25		88.53
250	250	30		83.49	250	250	30		89.17

Table H.4: Expected OPA at Different Combinations of Control Limits in TAL-TRL Scenario

HL_TAL	RL_TAL	CL_TRL	DR	OPA
50	50	50	EDD	69.87
50	50	100		70.41
50	50	150		71.01
50	50	200		71.24
50	50	250		70.66
50	150	50		87.57
50	150	100		89.25
50	150	150		90.82
50	150	200		91.87
50	150	250		91.96
50	250	50		85.12
50	250	100		87.46
50	250	150		89.55
50	250	200		90.96
50	250	250		91.25
150	50	50	EDD	69.61
150	50	100		69.75
150	50	150		70.18
150	50	200		70.46
150	50	250		70.16
150	150	50		86.65
150	150	100		88.08
150	150	150		89.64
150	150	200		90.91
150	150	250		91.44
150	250	50		81.53
150	250	100		83.79
150	250	150		86.03
150	250	200		87.81
150	250	250		88.70
250	50	50	EDD	70.65
250	50	100		70.40
250	50	150		70.66
250	50	200		71.01
250	50	250		71.01
250	150	50		85.67
250	150	100		86.86
250	150	150		88.42
250	150	200		89.91
250	150	250		90.89
250	250	50		76.52
250	250	100		78.70
250	250	150		81.09
250	250	200		83.26
250	250	250		84.78

HL_TAL	RL_TAL	CL_TRL	DR	OPA
50	50	50	S/OPN	69.91
50	50	100		70.00
50	50	150		70.64
50	50	200		71.38
50	50	250		71.80
50	150	50		89.77
50	150	100		90.48
50	150	150		91.59
50	150	200		92.65
50	150	250		93.23
50	250	50		88.47
50	250	100		89.36
50	250	150		90.47
50	250	200		91.39
50	250	250		91.68
150	50	50	S/OPN	69.50
150	50	100		69.47
150	50	150		70.22
150	50	200		71.31
150	50	250		72.31
150	150	50		89.33
150	150	100		90.09
150	150	150		91.47
150	150	200		93.03
150	150	250		94.35
150	250	50		86.01
150	250	100		87.10
150	250	150		88.65
150	250	200		90.23
150	250	250		91.41
250	50	50	S/OPN	70.52
250	50	100		70.39
250	50	150		71.27
250	50	200		72.71
250	50	250		74.29
250	150	50		88.97
250	150	100		89.78
250	150	150		91.45
250	150	200		93.53
250	150	250		95.60
250	250	50		82.27
250	250	100		83.57
250	250	150		85.57
250	250	200		87.83
250	250	250		89.92

Appendix I

Accuracy of the Regression Models of Chapter 5

This appendix contains reports on the accuracy of all the regression models from Chapter 5.

I.1 BUS Accept/Reject Rule, Regular Orders Only

To test the accuracy of the regression model built, the predicted values of OPA from the regression model have been compared with those obtained from the corresponding simulation model for the same set of values for the environmental variables and control parameters. In each case, the simulation is run for 5 replications each of length 83520 hours with the warm-up period of 11520 hours so that the half-width of the confidence interval of the mean of OPA is less than or equal to 1% of the mean. The results are shown in **Table I.1**. The "% Error" column in this and all subsequent tables of this appendix shows the errors in the regression model estimates, as a percentage of the values obtained from the simulation.

Table I.1: Accuracy for the BUS Regular Orders Only Case

Input Set of Variables					OPA		
DL	DLV	PTV	DDT[1]	RL	from Simulation	from Regression	% Error
0.75	0.1	0.1	1	30.64	99.33	99.86	0.5
0.85	0.1	0.1	1	29.05	95.67	95.61	-0.1
0.95	0.1	0.1	1	22.58	87.64	86.59	-1.2
0.85	0.6	0.1	1	28.54	94.87	94.44	-0.5
0.85	1.0	0.1	1	30.54	93.35	93.37	0.0
0.85	0.1	0.3	1	28.04	94.06	94.16	0.1
0.85	0.1	0.1	2	20.27	93.23	88.60	-5.0

This test for accuracy has been further expanded for the following scenarios which are generated from the following levels of the factors: DL={0.8, 0.9}, DLV={0.325, 0.775}, PTV=0.2, PUO=0, DDT={"Loose", "Tight"}, and RL=16. For this expanded test, the levels of the environmental factors are chosen to be at the middle of the levels at which the regression model has been originally calibrated. The results are shown in **Table I.2**.

1 In all tables of this appendix, the "Loose" and "Tight" levels of DDT are denoted by 1 and 2 respectively.

Table I.2: Accuracy for the BUS Regular Orders Only Case (Expanded Test)

Input Set of Variables					OPA		
DL	**DLV**	**PTV**	**DDT**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.80	0.325	0.2	1	16	91.85	96.93	5.5
0.80	0.325	0.2	2	16	89.16	88.01	-1.3
0.80	0.775	0.2	1	16	90.21	94.74	5.0
0.80	0.775	0.2	2	16	87.49	86.05	-1.6
0.90	0.325	0.2	1	16	86.36	91.19	5.6
0.90	0.325	0.2	2	16	82.44	78.57	-4.7
0.90	0.775	0.2	1	16	84.93	89.41	5.3
0.90	0.775	0.2	2	16	81.08	77.02	-5.0

I.2 BUS Accept/Reject Rule, Two Order Classes

Tests were conducted in a similar fashion to those for the regular orders only scenario. The results are shown in **Table I.3**.

Table I.3: Accuracy for the BUS Two Order Classes Case

Input Set of Variables							OPA		
DL	**DLV**	**PTV**	**PUO**	**DDT**	**HL**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.75	0.1	0.1	0.05	1	17.19	26.65	98.37	99.05	0.7
0.85	0.1	0.1	0.05	1	30.52	27.34	95.31	95.00	-0.3
0.95	0.1	0.1	0.05	1	30.89	24.63	88.65	88.78	0.1
0.85	1.0	0.1	0.05	1	31.04	27.52	92.95	92.80	-0.2
0.85	1.0	0.3	0.05	1	31.13	27.25	93.67	93.59	-0.1
0.85	0.1	0.1	0.25	1	29.96	25.71	93.84	93.21	-0.7
0.85	0.1	0.1	0.05	2	38.33	18.22	90.82	92.59	1.9

The test for accuracy has been further expanded as in the previous case. Various scenarios for the test were generated from the factor levels: DL={0.8, 0.9}, DLV={0.325, 0.775}, PTV=0.2, PUO={0.1, 0.2}, DDT={"Loose", "Tight"}, HL=24 and RL=16. The corresponding results are shown in the immediately following **Table I.4**.

Table I.4: Accuracy for the BUS Two Order Classes Case (Expanded Test)

Input Set of Variables							**OPA**		
DL	**DLV**	**PTV**	**PUO**	**DDT**	**HL**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.80	0.325	0.2	0.10	1	24	16	92.03	90.28	-1.9
0.80	0.325	0.2	0.10	2	24	16	87.23	86.24	-1.1
0.80	0.325	0.2	0.20	1	24	16	92.27	91.42	-0.9
0.80	0.325	0.2	0.20	2	24	16	84.97	84.25	-0.9
0.80	0.775	0.2	0.10	1	24	16	90.52	88.68	-2.0
0.80	0.775	0.2	0.10	2	24	16	85.56	84.37	-1.4
0.80	0.775	0.2	0.20	1	24	16	90.57	89.82	-0.8
0.80	0.775	0.2	0.20	2	24	16	83.16	82.35	-1.0
0.90	0.325	0.2	0.10	1	24	16	86.71	85.46	-1.4
0.90	0.325	0.2	0.10	2	24	16	80.01	79.40	-0.8
0.90	0.325	0.2	0.20	1	24	16	86.82	85.99	-1.0
0.90	0.325	0.2	0.20	2	24	16	77.30	77.16	-0.2
0.90	0.775	0.2	0.10	1	24	16	85.20	83.98	-1.4
0.90	0.775	0.2	0.10	2	24	16	78.58	78.09	-0.6
0.90	0.775	0.2	0.20	1	24	16	85.46	84.52	-1.1
0.90	0.775	0.2	0.20	2	24	16	75.98	75.82	-0.2

I.3 TAL Accept/Reject Rule, Regular Orders Only

Test were conducted in a similar fashion to those for the BUS rule. The corresponding results are in **Table I.5**.

Table I.5: Accuracy for the TAL Regular Orders Only Case

Input Set of Variables					**OPA**		
DL	**DLV**	**PTV**	**DDT**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.75	0.1	0.1	1	133.66	98.99	97.81	-1.2
0.85	0.1	0.1	1	134.91	92.68	92.43	-0.3
0.95	0.1	0.1	1	134.42	83.35	84.35	1.2
0.85	0.6	0.1	1	138.07	91.53	92.25	0.8
0.85	1.0	0.1	1	141.93	89.63	91.01	1.5
0.85	0.1	0.3	1	131.80	90.76	90.99	0.3
0.85	0.1	0.1	2	87.94	77.23	78.16	1.2

This comparison has also been further expanded for the scenarios which are generated from the factor levels: DL={0.8, 0.9}, DLV={0.325, 0.775}, PTV=0.2, PUO={0.1, 0.2}, DDT={"Loose", "Tight"} and RL={125, 225}. The results are shown in **Table I.6**.

Table I.6: Accuracy for the TAL Regular Orders Only Case (Expanded Test)

Input Set of Variables					OPA		
DL	**DLV**	**PTV**	**DDT**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.80	0.325	0.2	1	125	96.18	92.21	-8.2
0.80	0.325	0.2	1	225	96.33	87.87	-17.5
0.80	0.325	0.2	2	125	81.76	74.78	-17.0
0.80	0.325	0.2	2	225	76.94	55.83	-54.6
0.80	0.775	0.2	1	125	93.97	91.55	-5.1
0.80	0.775	0.2	1	225	93.80	85.97	-16.6
0.80	0.775	0.2	2	125	81.52	74.77	-16.5
0.80	0.775	0.2	2	225	71.23	52.99	-51.0
0.90	0.325	0.2	1	125	87.40	91.87	10.2
0.90	0.325	0.2	1	225	76.85	87.56	27.7
0.90	0.325	0.2	2	125	68.65	74.31	16.4
0.90	0.325	0.2	2	225	28.40	55.82	192.1
0.90	0.775	0.2	1	125	86.36	91.47	11.8
0.90	0.775	0.2	1	225	79.24	85.94	16.8
0.90	0.775	0.2	2	125	70.35	74.11	10.6
0.90	0.775	0.2	2	225	36.19	52.81	91.4

I.4 TAL Accept/Reject Rule, Two Order Classes

Test were conducted in a similar fashion to those for the BUS rule. The results are shown in **Table I.7**.

Table I.7: Accuracy for the TAL Two Order Classes Case

Input Set of Variables							OPA		
DL	**DLV**	**PTV**	**PUO**	**DDT**	**HL**	**RL**	**from Simulation**	**from Regression**	**% Error**
0.75	0.1	0.1	0.05	1	110.53	198.66	98.99	99.98	1.0
0.85	0.1	0.1	0.05	1	125.35	144.03	92.68	94.61	2.1
0.95	0.1	0.1	0.05	1	121.62	120.32	83.35	83.92	0.7
0.85	1.0	0.1	0.05	1	126.26	146.69	89.63	92.72	3.4
0.85	1.0	0.3	0.05	1	120.69	134.35	90.76	92.49	1.9
0.85	0.1	0.1	0.25	1	156.94	126.57	90.36	91.29	1.0
0.85	0.1	0.1	0.05	2	73.36	176.17	73.38	77.59	5.7

This comparison has also been further expanded for the scenarios which are generated from the factor levels: DL={0.8, 0.9}, DLV={0.325, 0.775}, PTV=0.2, PUO={0.1, 0.2}, DDT={"Loose", "Tight"}, RL={125, 225} and RL={125, 225}. The results are shown in **Table I.8.**

Table I.8: Accuracy for the TAL Two Order Classes Case (Expanded Test)

Input Set of Variables							OPA		
DL	DLV	PTV	PUO	DDT	HL	RL	from Simulation	from Regression	% Error
0.80	0.325	0.2	0.10	1	125	125	95.77	95.98	0.2
0.80	0.325	0.2	0.10	1	125	225	95.60	94.91	-0.7
0.80	0.325	0.2	0.10	1	225	125	95.64	94.55	-1.1
0.80	0.325	0.2	0.10	1	225	225	95.36	93.84	-1.6
0.80	0.325	0.2	0.10	2	125	125	78.62	89.04	13.3
0.80	0.325	0.2	0.10	2	125	225	77.13	98.24	27.4
0.80	0.325	0.2	0.10	2	225	125	79.00	87.03	10.2
0.80	0.325	0.2	0.10	2	225	225	73.68	90.28	22.5
0.80	0.325	0.2	0.20	1	125	125	95.01	93.63	-1.5
0.80	0.325	0.2	0.20	1	125	225	94.80	92.86	-2.0
0.80	0.325	0.2	0.20	1	225	125	94.94	93.87	-1.1
0.80	0.325	0.2	0.20	1	225	225	94.21	91.65	-2.7
0.80	0.325	0.2	0.20	2	125	125	76.19	86.62	13.7
0.80	0.325	0.2	0.20	2	125	225	75.36	98.74	31.0
0.80	0.325	0.2	0.20	2	225	125	75.90	82.63	8.9
0.80	0.325	0.2	0.20	2	225	225	70.42	87.01	23.6
0.80	0.775	0.2	0.10	1	125	125	93.42	94.36	1.0
0.80	0.775	0.2	0.10	1	125	225	93.64	93.29	-0.4
0.80	0.775	0.2	0.10	1	225	125	93.38	92.59	-0.8
0.80	0.775	0.2	0.10	1	225	225	93.00	92.14	-0.9
0.80	0.775	0.2	0.10	2	125	125	78.80	87.25	10.7
0.80	0.775	0.2	0.10	2	125	225	74.72	95.81	28.2
0.80	0.775	0.2	0.10	2	225	125	78.28	85.25	8.9
0.80	0.775	0.2	0.10	2	225	225	67.49	88.13	30.6
0.80	0.775	0.2	0.20	1	125	125	92.80	92.19	-0.7
0.80	0.775	0.2	0.20	1	125	225	93.09	91.21	-2.0
0.80	0.775	0.2	0.20	1	225	125	93.13	92.14	-1.1
0.80	0.775	0.2	0.20	1	225	225	92.11	89.99	-2.3
0.80	0.775	0.2	0.20	2	125	125	75.74	84.92	12.1
0.80	0.775	0.2	0.20	2	125	225	73.96	96.20	30.1
0.80	0.775	0.2	0.20	2	225	125	75.44	81.02	7.4
0.80	0.775	0.2	0.20	2	225	225	64.09	84.81	32.3
0.90	0.325	0.2	0.10	1	125	125	86.72	88.33	1.9
0.90	0.325	0.2	0.10	1	125	225	84.09	82.80	-1.5

Table I.8 (contd.): Accuracy for the TAL Two Order Classes Case (Expanded Test)

Input Set of Variables							OPA		
DL	DLV	PTV	PUO	DDT	HL	RL	from Simulation	from Regression	% Error
0.90	0.325	0.2	0.10	1	225	225	74.69	77.11	3.2
0.90	0.325	0.2	0.10	2	125	125	64.75	75.57	16.7
0.90	0.325	0.2	0.10	2	125	225	55.48	72.93	31.5
0.90	0.325	0.2	0.10	2	225	125	64.58	70.69	9.5
0.90	0.325	0.2	0.10	2	225	225	24.98	57.94	131.9
0.90	0.325	0.2	0.20	1	125	125	85.61	86.47	1.0
0.90	0.325	0.2	0.20	1	125	225	84.44	83.25	-1.4
0.90	0.325	0.2	0.20	1	225	125	85.82	84.53	-1.5
0.90	0.325	0.2	0.20	1	225	225	72.03	75.70	5.1
0.90	0.325	0.2	0.20	2	125	125	61.41	75.35	22.7
0.90	0.325	0.2	0.20	2	125	225	58.30	77.65	33.2
0.90	0.325	0.2	0.20	2	225	125	60.93	66.77	9.6
0.90	0.325	0.2	0.20	2	225	225	20.89	57.16	173.6
0.90	0.775	0.2	0.10	1	125	125	85.71	87.33	1.9
0.90	0.775	0.2	0.10	1	125	225	82.68	82.65	0.0
0.90	0.775	0.2	0.10	1	225	125	85.40	85.93	0.6
0.90	0.775	0.2	0.10	1	225	225	77.09	77.70	0.8
0.90	0.775	0.2	0.10	2	125	125	67.31	75.74	12.5
0.90	0.775	0.2	0.10	2	125	225	52.02	73.31	40.9
0.90	0.775	0.2	0.10	2	225	125	66.56	71.69	7.7
0.90	0.775	0.2	0.10	2	225	225	31.41	59.41	89.2
0.90	0.775	0.2	0.20	1	125	125	84.68	85.37	0.8
0.90	0.775	0.2	0.20	1	125	225	83.44	82.80	-0.8
0.90	0.775	0.2	0.20	1	225	125	85.03	83.97	-1.2
0.90	0.775	0.2	0.20	1	225	225	75.26	76.05	1.0
0.90	0.775	0.2	0.20	2	125	125	64.14	75.34	17.5
0.90	0.775	0.2	0.20	2	125	225	58.17	77.65	33.5
0.90	0.775	0.2	0.20	2	225	125	63.05	67.66	7.3
0.90	0.775	0.2	0.20	2	225	225	28.20	58.31	106.8

I.5 SIMUL Accept/Reject Rule Regular Orders Only

It was not possible to carry out this test due to unavailability of resources.

I.6 SIMUL Accept/Reject Rule, Two Order Classes

Test were conducted in a similar fashion to those for the BUS rule. The results are shown in the **Table I.9**.

Table I.9: Accuracy for the SIMUL Two Order Classes Case

Input Set of Variables						OPA		
DL	DLV	PTV	PUO	DDT	Kincr	from Simulation	from Regression	% Error
0.75	0.1	0.1	0.05	1	0.783	98.85	99.59	0.7
0.85	0.1	0.1	0.05	1	0.762	94.91	99.56	4.9
0.95	0.1	0.1	0.05	1	0.854	97.70	87.82	-10.1
0.85	1.0	0.1	0.05	1	0.835	93.25	97.86	4.9
0.85	1.0	0.3	0.05	1	0.779	93.05	98.17	5.5
0.85	0.1	0.1	0.25	1	0.902	92.91	97.45	4.9
0.85	0.1	0.1	0.05	2	0.812	86.47	94.34	9.1

An expanded test for accuracy of the regression model in this case was not done due to time and resource constraints.

I.7 Comments on the Accuracy of the Regression Models

From the results of the above tests the following observations and comments can be made.

(1) As might be expected, the regression model predicted values of OPA closely match the values obtained from simulations for combinations of environmental factors which were set in the simulations used to build the regression model in the first place.

(2) In the two order classes scenario of the BUS and TAL AR rules, the regression models were built based on a much larger set of design points than the D-optimal design would have suggested. As a result the accuracy of these regression models is

reasonably good, even at the points away from the scenarios where the regression models have been calibrated. However, it should be noted that for the scenarios involving a "Tight" level of DDT, the regression model for the TAL case still performs poorly. This suggests that more design points involving the "Tight" level of DDT should be used in building an improved regression model for the TAL two classes of order case.

(3) The regression model for the SIMUL rule, two classes of order case is poor. This can be attributed to the following two reasons. Firstly, the observations of OPA at different design points are biased because insufficiently long simulation runs were used to obtain these observations (due to time and resource constraints). Secondly, the number of design points used by the D-optimal design was insufficient to build a good regression model.

The regression model corresponding to the SIMUL regular orders only scenario could not be tested, again due to the time and resource problem. But it is likely poor due to the same two reasons as explained above in the case of two classes of order.

Appendix J

Main Performances at Optimal Control

This appendix contains the plots and the corresponding tabular data showing how the main performance measures of the system vary in case of each accept/reject rule, with one of the environmental factors changing and other factors remaining at their base levels, and when the system is controlled optimally. The data for each of these quantities, which are plotted here, were obtained by averaging five observations of the respective quantity. These five observations are obtained by simulating the system with above conditions for 5 replications, each replication being of length 83520 hours which includes a warm-up period of 11520 hours such that the half-width of the confidence interval around the average is within 1% of the average.

The plots of the results have been presented in three sections *viz.* **J.1**, **J.2**, **J.3**, which are devoted to BUS, TAL and SIMUL accept/reject rule respectively. The corresponding tabulated data have been presented in subsequent sections **J.4**, **J.5**, **J.6**.

J.1 Plots for the Main Performances When Bus Is Active

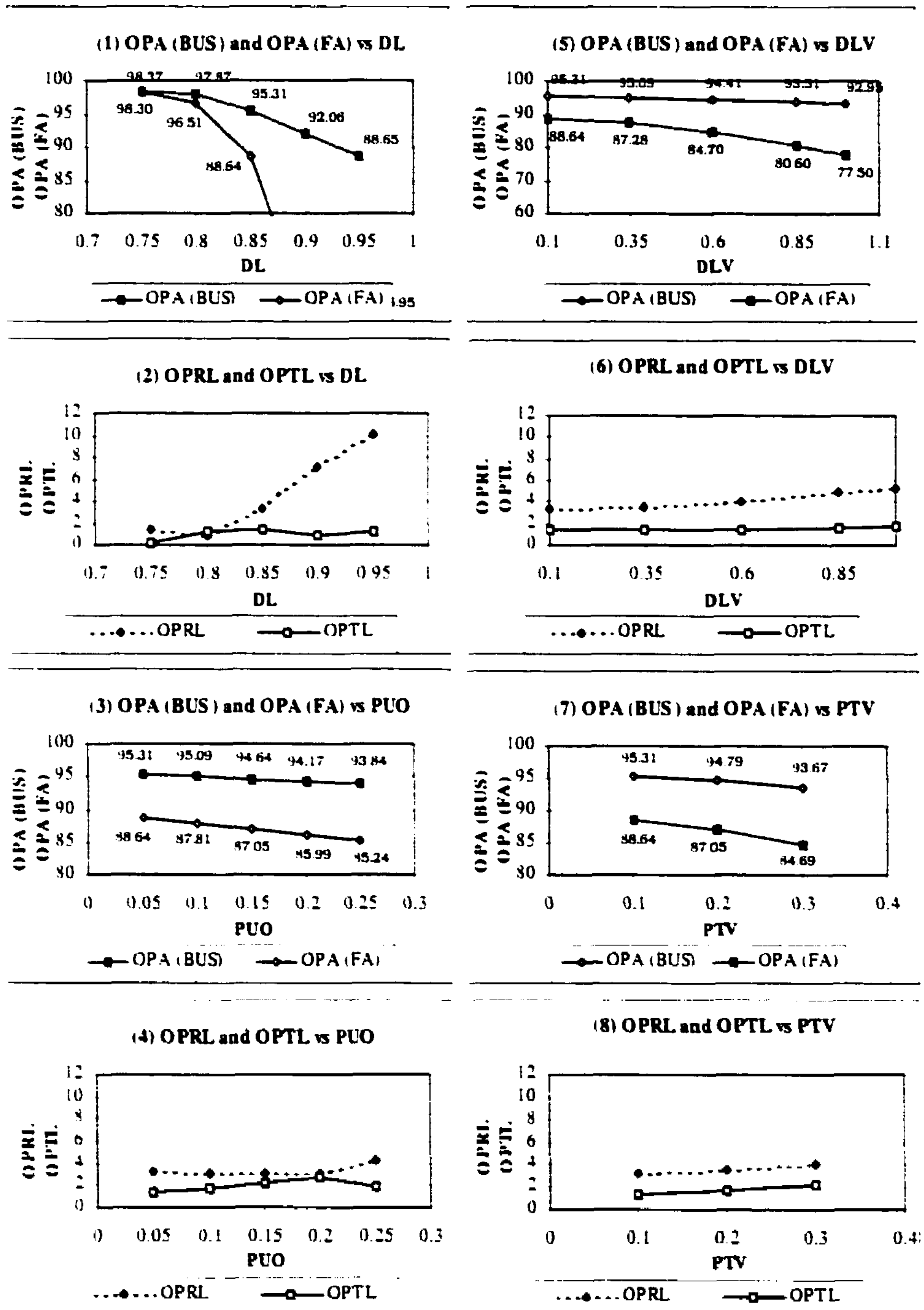

Figure J.1.1: Effect of Optimal Control on OPA, OPRL and OPTL under Changing DL, PUO, DLV and PTV, When BUS Is Active

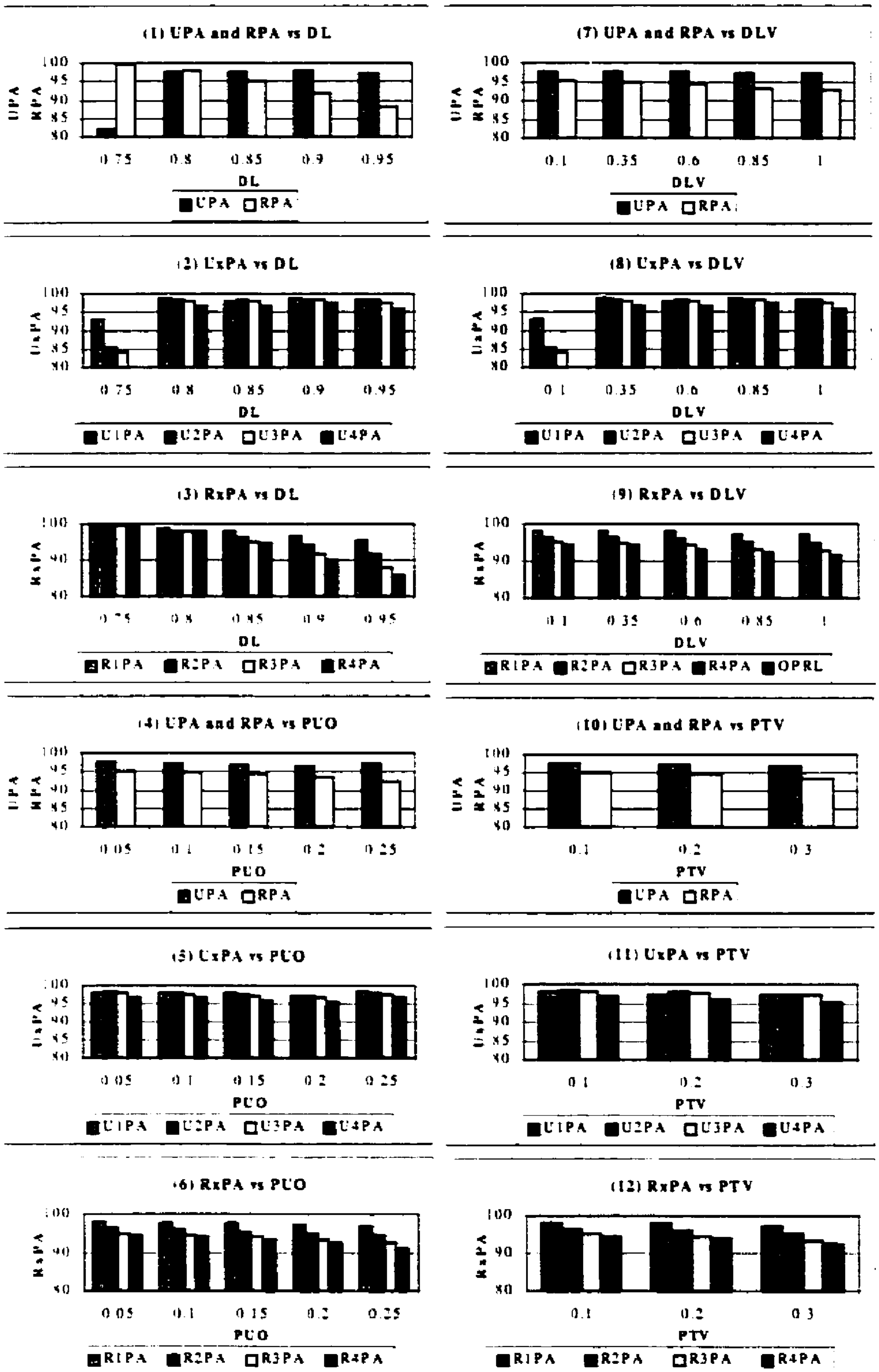

Figure J.1.2: Effect of Optimal Control on UPA, RPA, UxPA and RxPA under Changing DL, PUO, DLV and PTV, When BUS Is Active

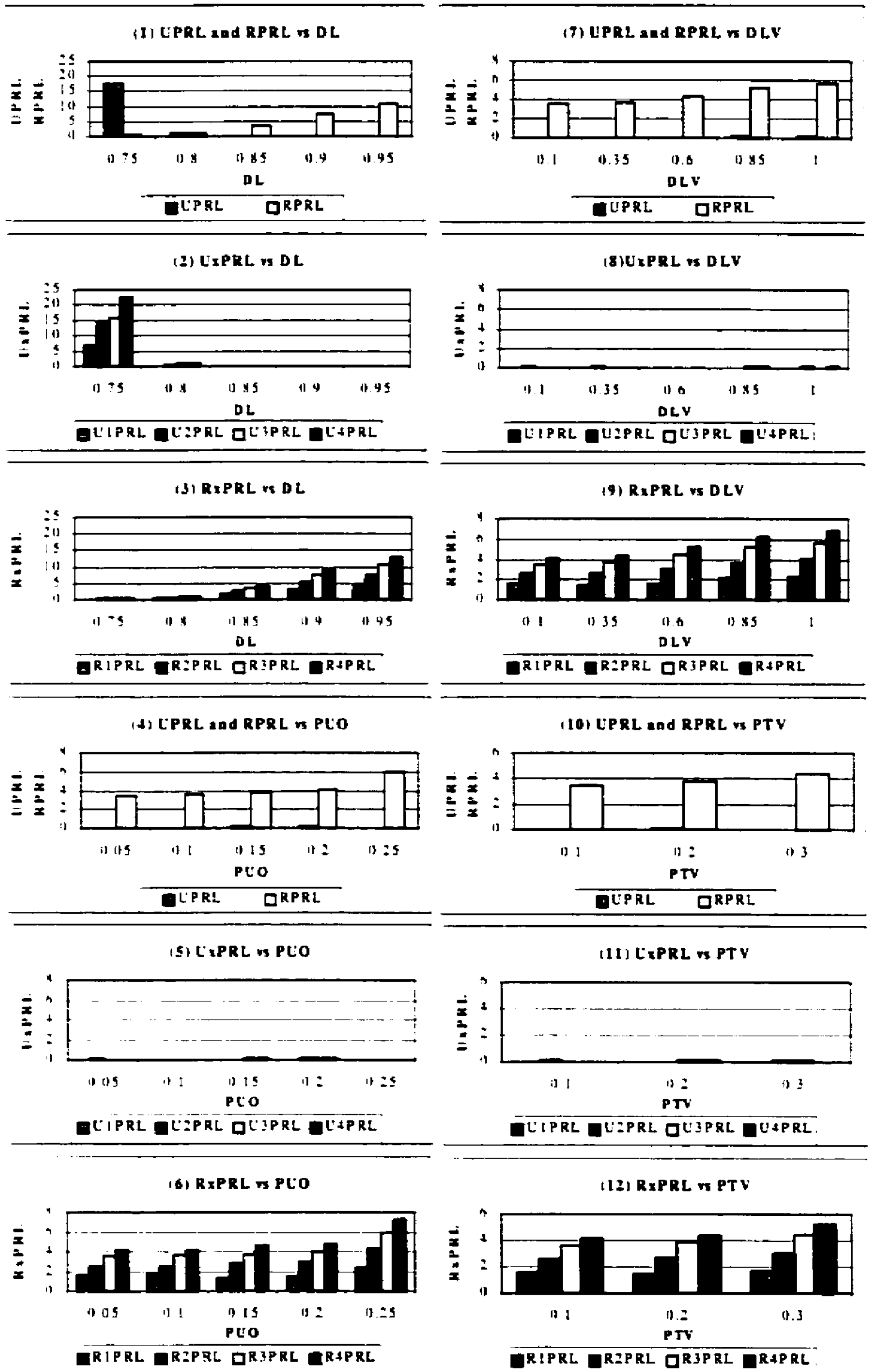

Figure J.1.3: Effect of Optimal Control on UPRL, RPRL, UxPRL, and RxPRL under Changing DL, PUO, DLV and PTV, When BUS Is Active

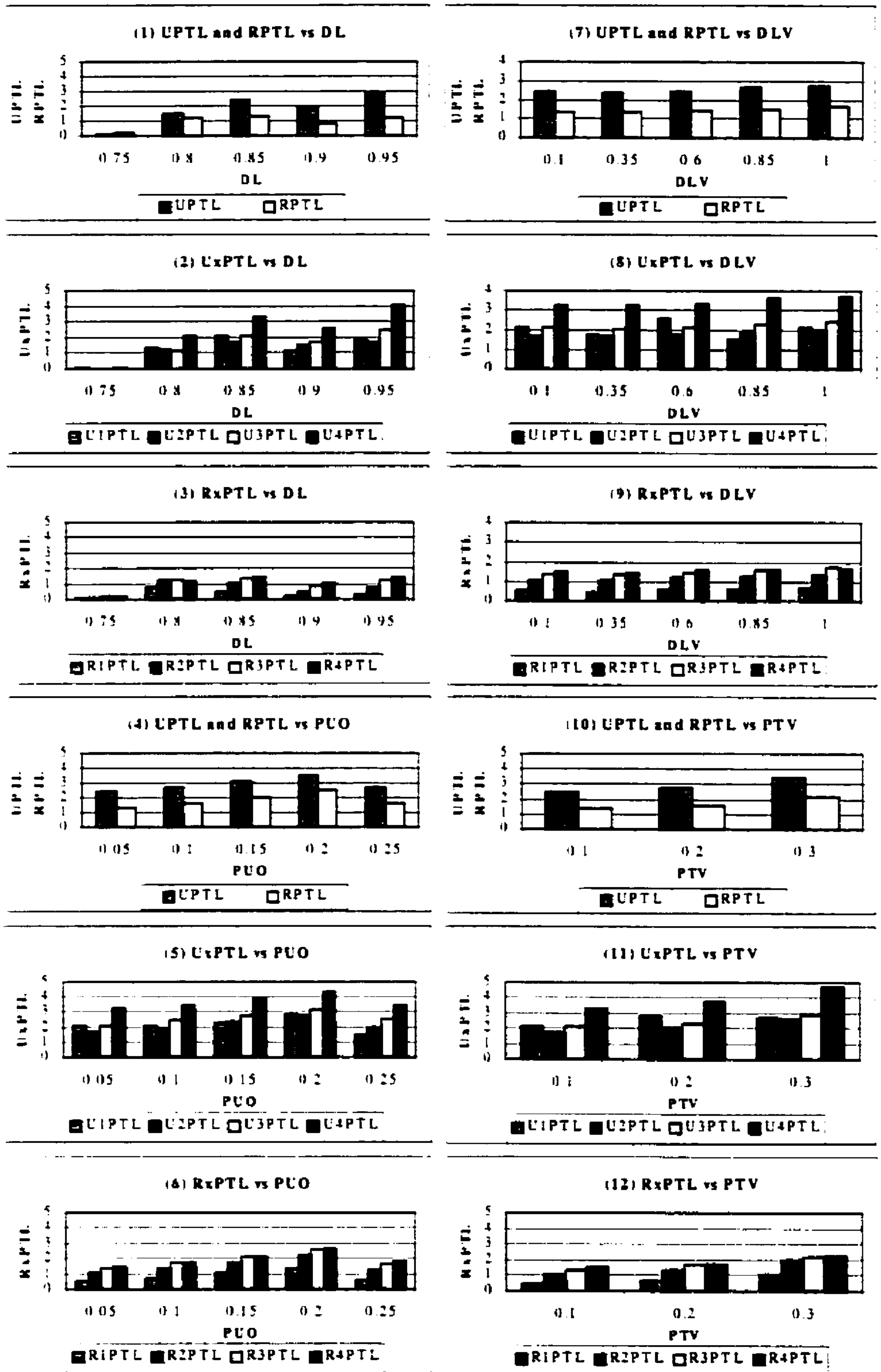

Figure J.1.4: Effect of Optimal Control on UPTL, RPTL, UxPTL, and RxPTL under Changing DL, PUO, DLV and PTV, When BUS Is Active

J.2 Plots for the Main Performances When TAL Is Active

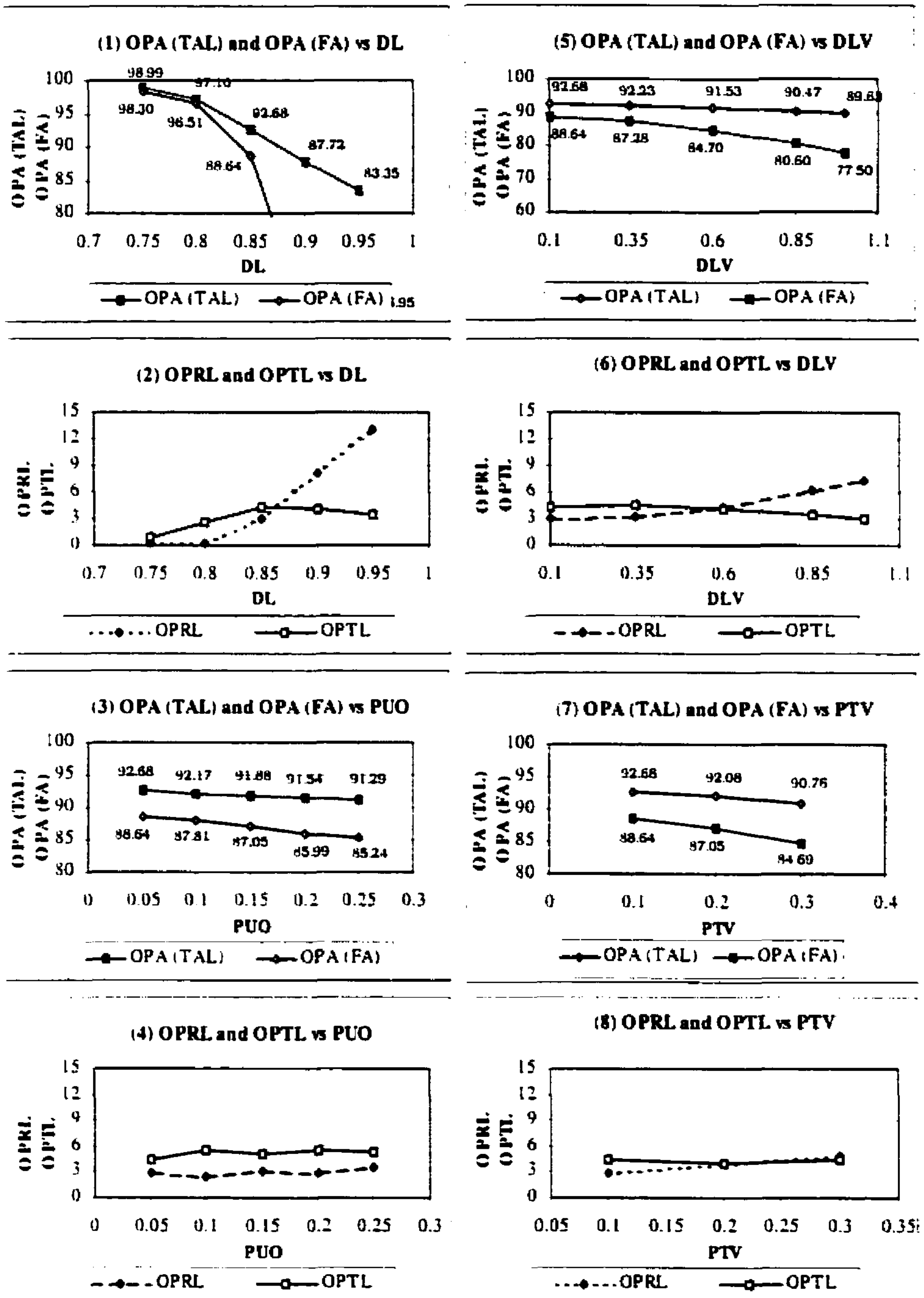

Figure J.2.1: Effect of Optimal Control on OPA, OPRL, and OPTL under Changing DL, PUO, DLV and PTV, When TAL Is Active

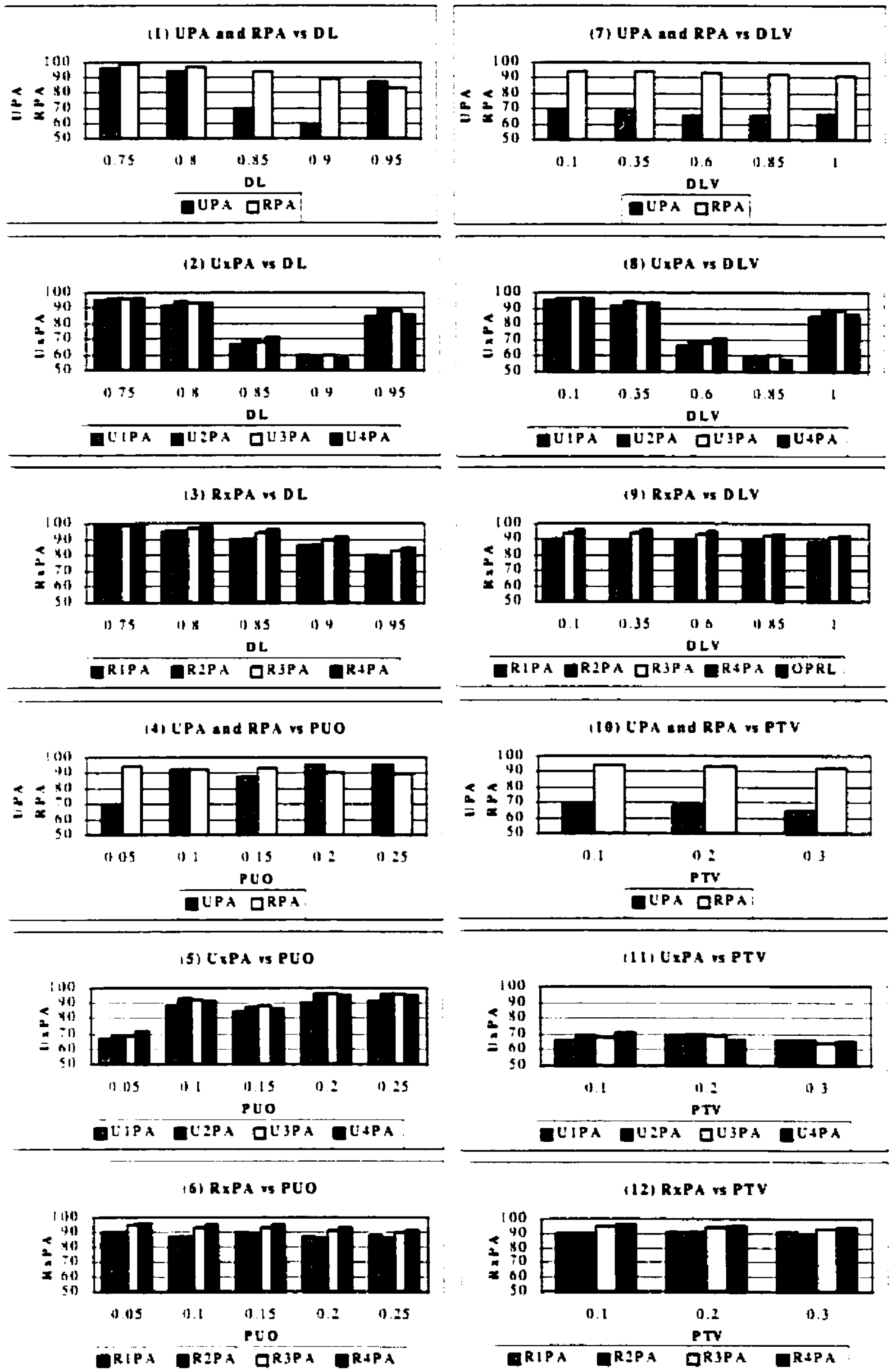

Figure J.2.2: Effect of Optimal Control on UPA, RPA, UxPA, and RxPA under Changing DL, PUO, DLV and PTV, When TAL Is Active

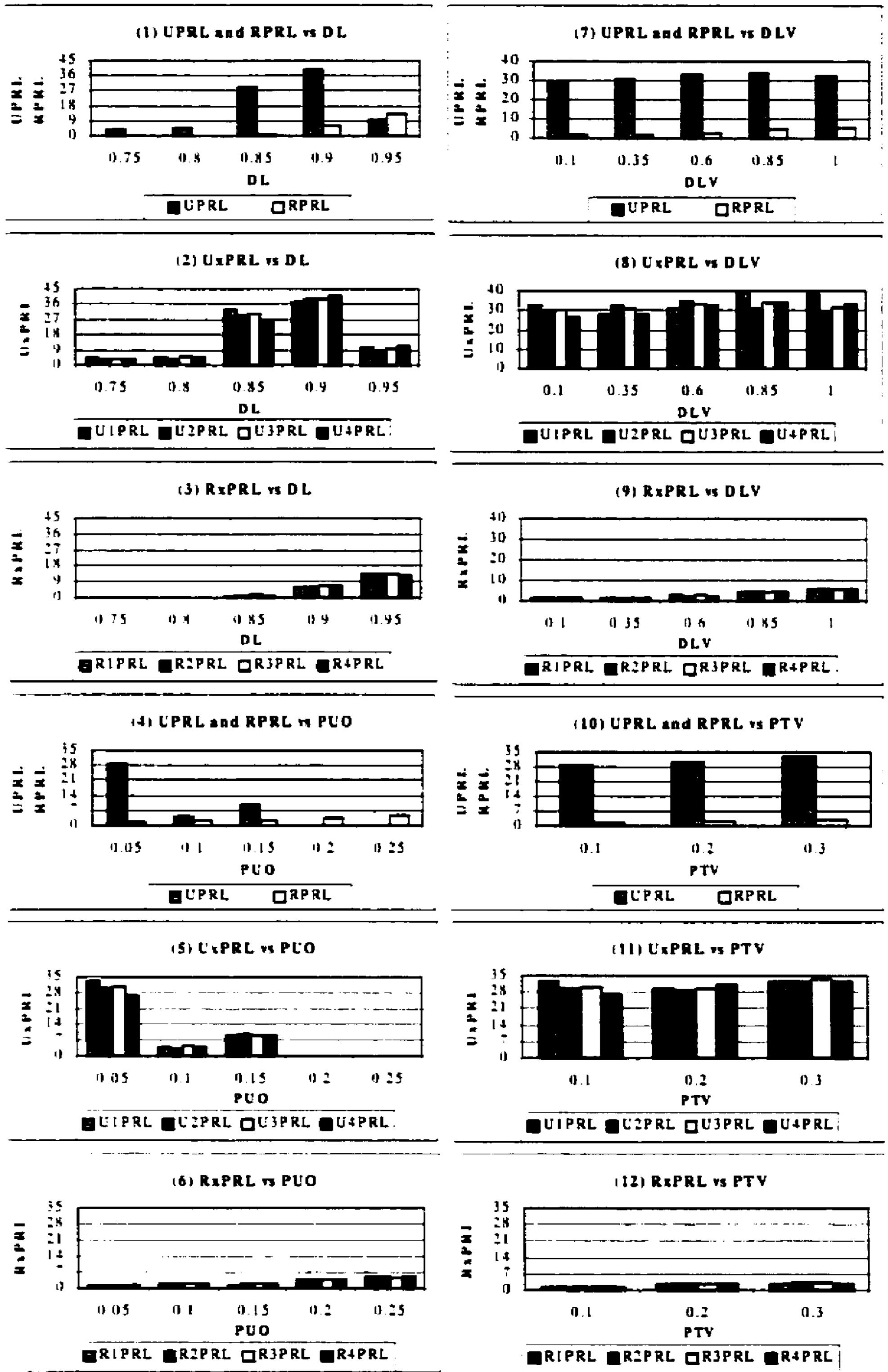

Figure J.2.3: Effect of Optimal Control on UPRL, RPRL, UxPRL, and RxPRL under Changing DL, PUO, DLV and PTV, When TAL Is Active

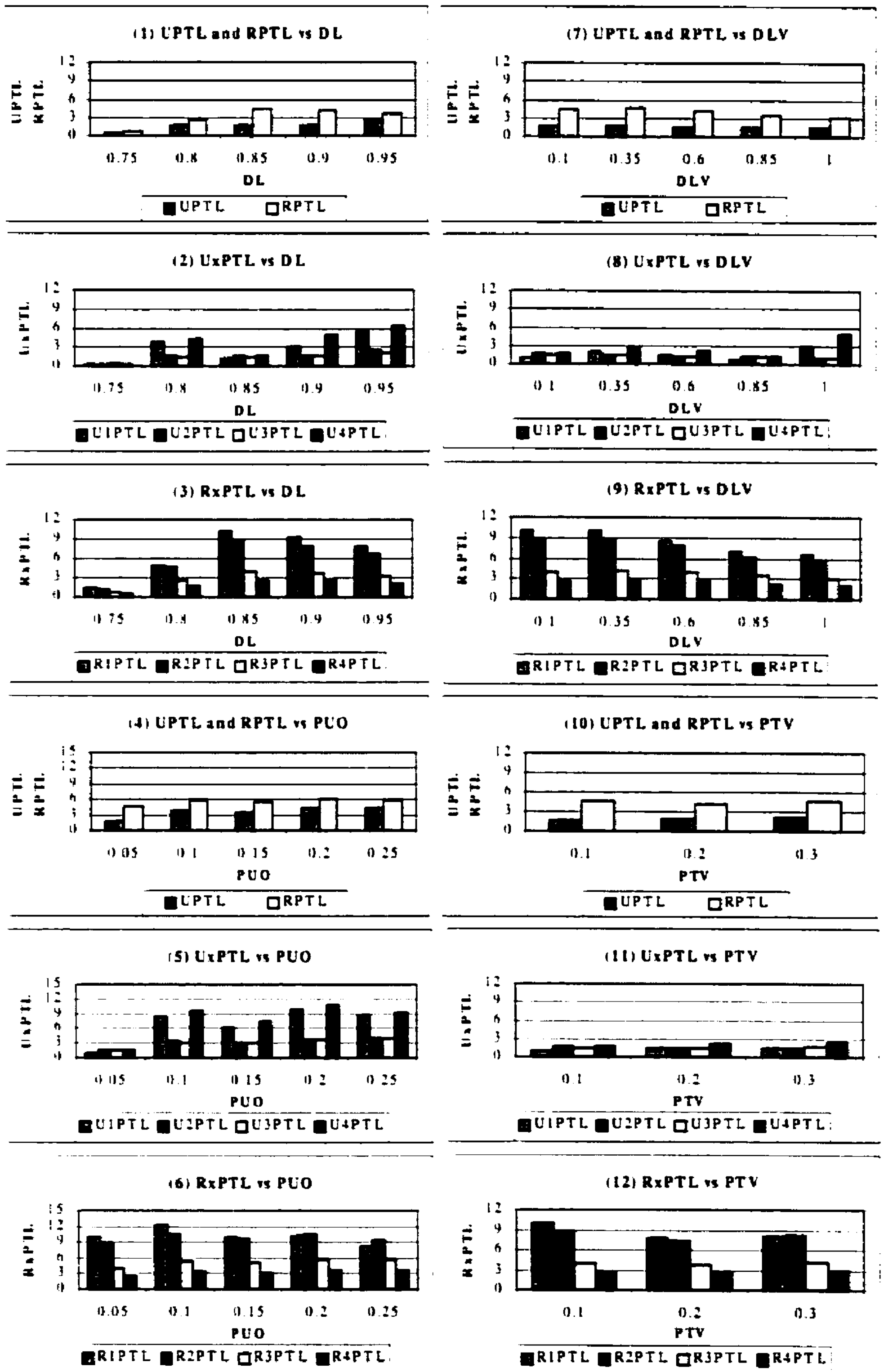

Figure J.2.4: Effect of Optimal Control on UPTL, RPTL, UxPTL, and RxPTL under Changing DL, PUO, DLV and PTV, When TAL Is Active

J.3 Plots for the Main Performances When SIMUL Is Active

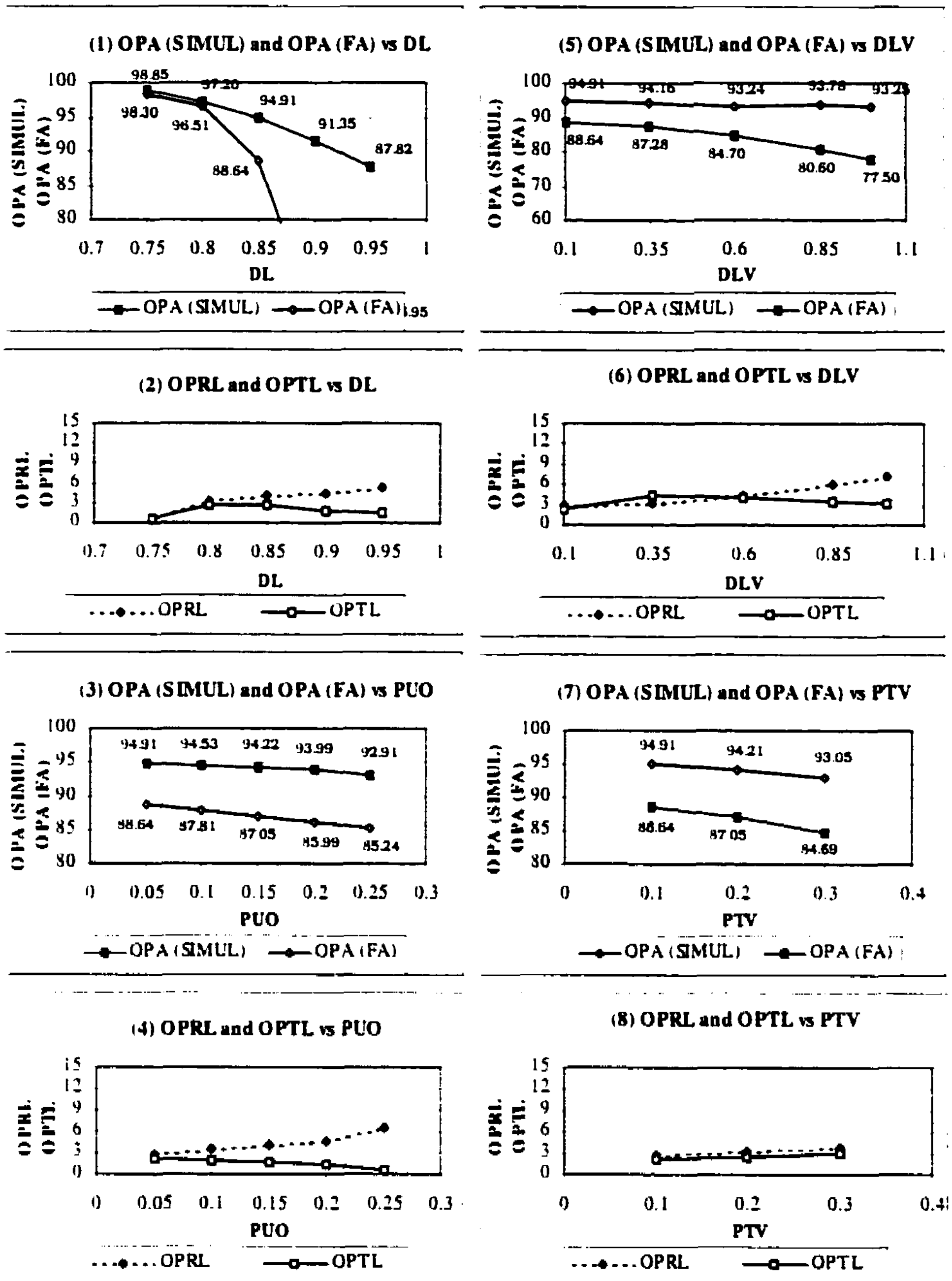

Figure J.3.1: Effect of Optimal Control on OPA, OPRL, and OPTL under Changing DL, PUO, DLV and PTV, When SIMUL Is Active

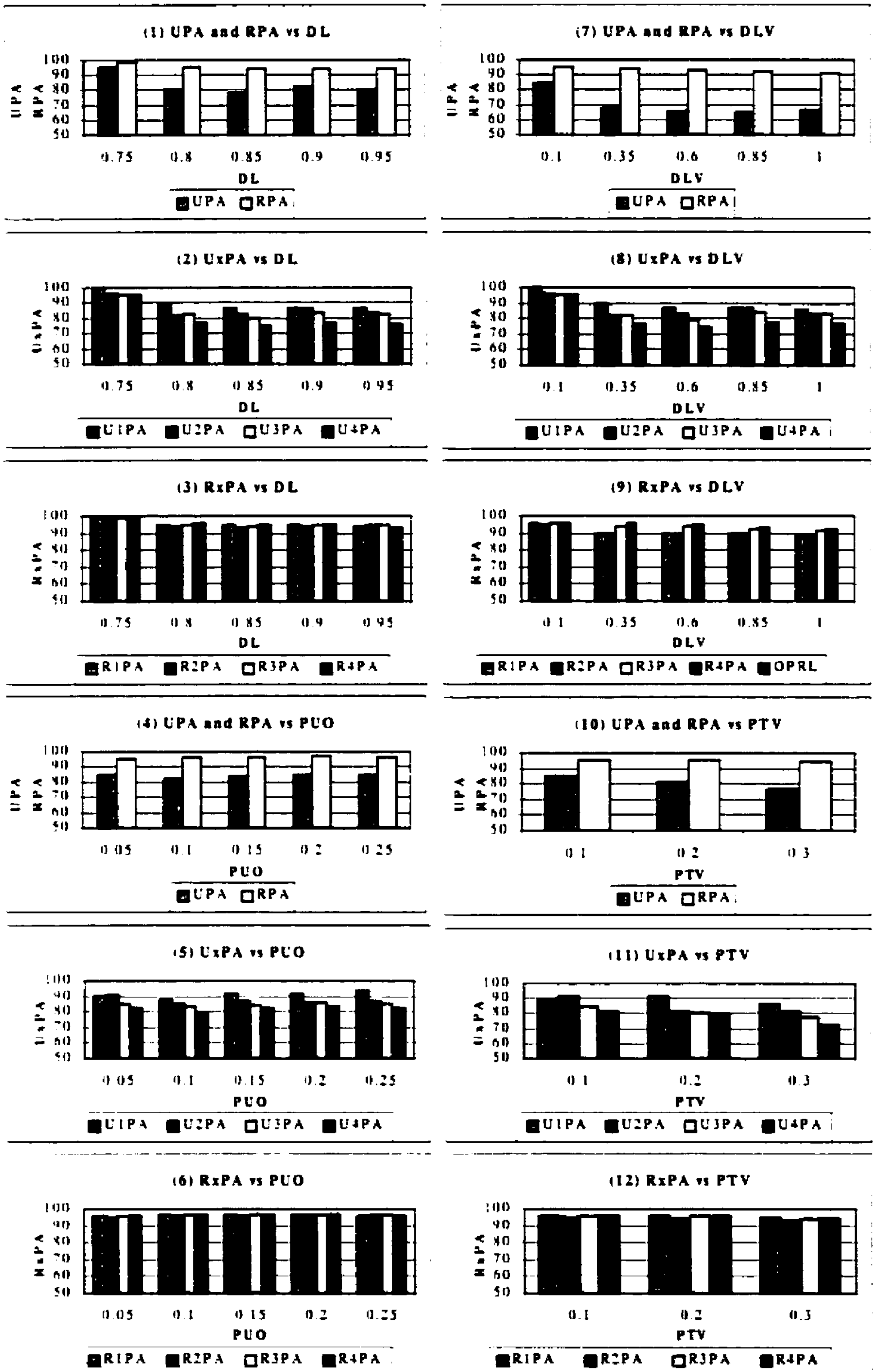

Figure J.3.2: Effect of Optimal Control on UPA, RPA, UxPA, and RxPA under Changing DL, PUO, DLV and PTV, When SIMUL Is Active

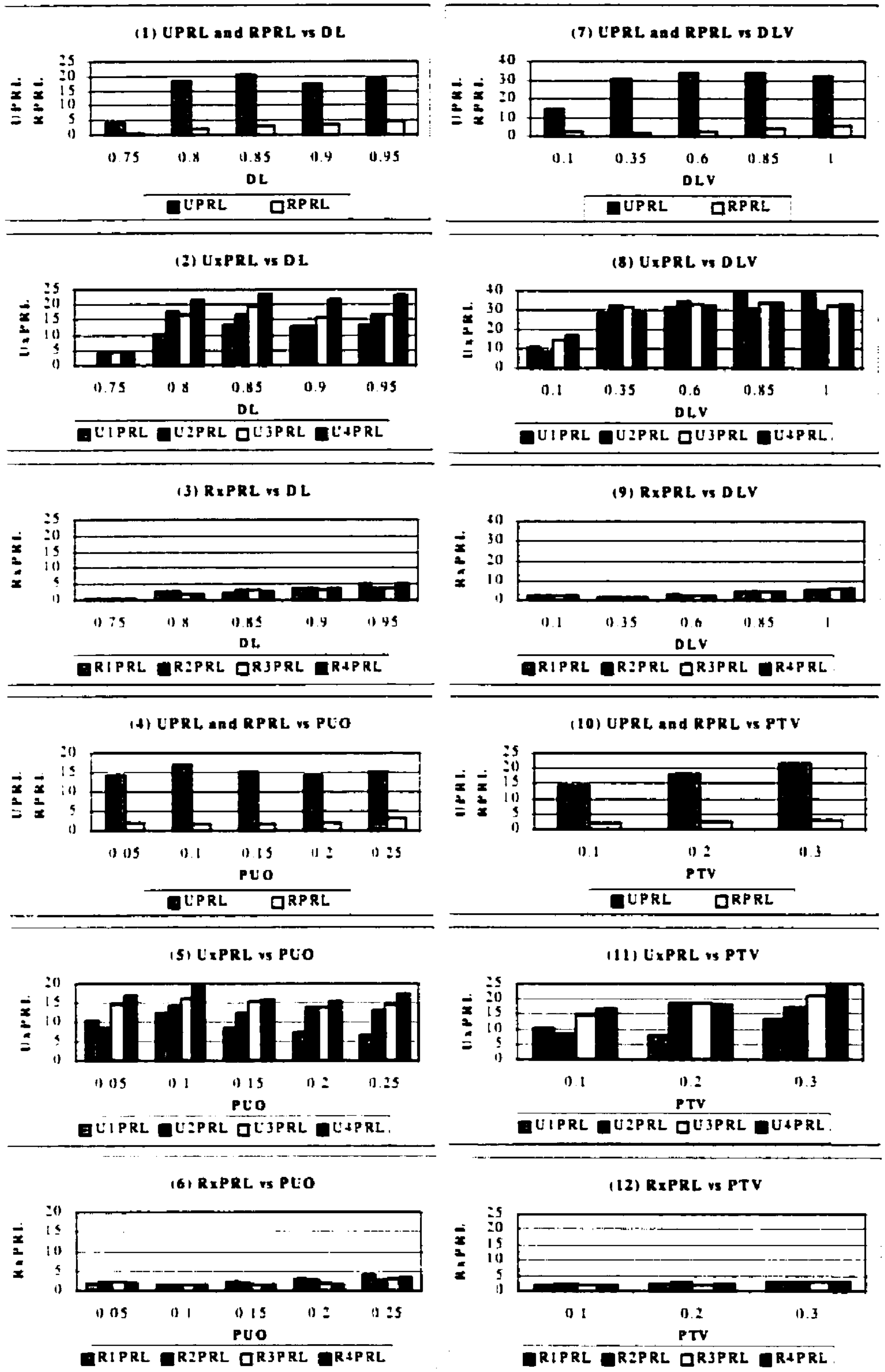

Figure J.3.3: Effect of Optimal Control on UPRL, RPRL, UxPRL, and RxPRL, under Changing DL, PUO, DLV and PTV, When SIMUL Is Active

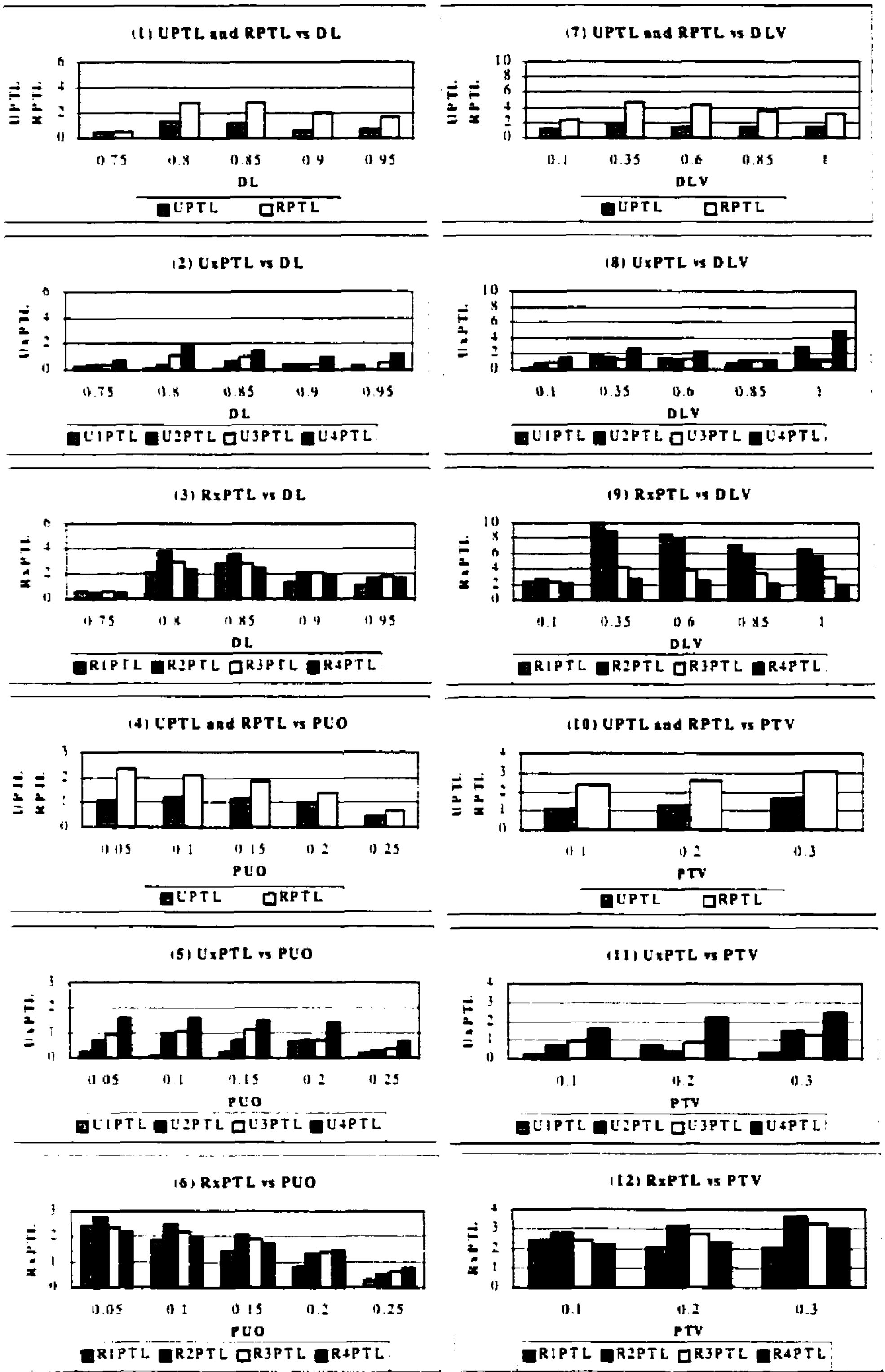

Figure J.3.4: Effect of Optimal Control on UPTL, RPTL, UxPTL, and RxPTL under Changing DL, PUO, DLV and PTV, When SIMUL Is Active

J.4 Tabulated Main Performance Measures When Bus Is Active

Table J.1: OPA, UPA, RPA, UxPA and RxPA under Changing DL, DLV, PTV and PUO, When BUS Is Active

DL	OPA	UPA	RPA	U1PA	U2PA	U3PA	U4PA	R1PA	R2PA	R3PA	R4PA
0.75	98.37	82.22	99.43	93.25	85.40	83.95	77.32	99.80	99.59	99.40	99.37
0.80	97.87	97.70	97.88	98.67	98.44	97.98	96.85	98.85	98.09	97.77	97.84
0.85	95.31	97.56	95.16	97.90	98.20	97.92	96.73	97.90	96.37	95.08	94.42
0.90	92.06	98.05	91.66	98.82	98.50	98.30	97.42	96.74	94.02	91.68	90.01
0.95	88.65	97.14	88.09	98.25	98.28	97.53	95.90	95.41	91.70	88.07	85.64
DLV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	95.31	97.56	95.16	97.90	98.20	97.92	96.73	97.90	96.37	95.08	94.42
0.35	95.09	97.57	94.93	98.26	98.23	97.87	96.77	98.01	96.30	94.78	94.17
0.60	94.41	97.53	94.21	97.43	98.30	97.90	96.65	97.83	95.82	94.09	93.23
0.85	93.51	97.26	93.26	98.51	98.09	97.63	96.24	97.20	95.05	93.17	92.14
1.00	92.95	97.17	92.67	97.91	97.94	97.53	96.22	97.00	94.56	92.56	91.49
PTV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	95.31	97.56	95.16	97.90	98.20	97.92	96.73	97.90	96.37	95.08	94.42
0.20	94.79	97.17	94.63	97.24	98.00	97.59	96.18	97.90	95.95	94.41	93.97
0.30	93.67	96.50	93.48	97.35	97.32	97.07	95.26	97.30	95.03	93.32	92.58
PUO	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.05	95.31	97.56	95.16	97.90	98.20	97.92	96.73	97.90	96.37	95.08	94.42
0.10	95.09	97.28	94.79	97.94	98.11	97.50	96.46	97.54	96.12	94.62	94.11
0.15	94.64	96.85	94.15	97.79	97.63	97.16	95.94	97.69	95.43	94.18	93.18
0.20	94.17	96.39	93.49	97.19	97.18	96.68	95.50	97.08	94.79	93.37	92.68
0.25	93.84	97.28	92.41	98.52	98.01	97.46	96.56	97.00	94.40	92.45	90.98

Table J.2: OPRL, UPRL, RPRL, UxPRL and RxPRL under Changing DL, DLV, PTV and PUO, When BUS Is Active

DL	OPRL	UPRL	RPRL	U1PRL	U2PRL	U3PRL	U4PRL	R1PRL	R2PRL	R3PRL	R4PRL
0.75	1.47	17.72	0.40	6.65	14.58	16.04	22.54	0.11	0.29	0.44	0.44
0.80	0.91	0.83	0.92	0.00	0.36	0.87	1.10	0.36	0.67	0.97	1.02
0.85	3.29	0.02	3.51	0.00	0.11	0.00	0.00	1.59	2.55	3.55	4.09
0.90	7.06	0.00	7.53	0.00	0.00	0.00	0.00	3.07	5.50	7.51	8.96
0.95	10.06	0.00	10.72	0.00	0.00	0.00	0.00	4.28	7.52	10.71	12.90
DLV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	3.29	0.02	3.51	0.00	0.11	0.00	0.00	1.59	2.55	3.55	4.09
0.35	3.51	0.05	3.73	0.00	0.11	0.07	0.00	1.53	2.61	3.84	4.36
0.60	4.11	0.00	4.38	0.00	0.00	0.00	0.00	1.60	3.00	4.46	5.22
0.85	4.89	0.10	5.21	0.00	0.00	0.13	0.11	2.16	3.66	5.21	6.25
1.00	5.37	0.09	5.72	0.00	0.11	0.07	0.11	2.36	4.08	5.74	6.81
PTV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	3.29	0.02	3.51	0.00	0.11	0.00	0.00	1.59	2.55	3.55	4.09
0.20	3.53	0.07	3.76	0.00	0.00	0.07	0.11	1.48	2.69	3.91	4.30
0.30	4.11	0.05	4.38	0.00	0.11	0.06	0.00	1.62	3.01	4.48	5.18
PUO	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.05	3.29	0.02	3.51	0.00	0.11	0.00	0.00	1.59	2.55	3.55	4.09
0.10	3.16	0.04	3.60	0.00	0.00	0.04	0.06	1.75	2.49	3.68	4.21
0.15	3.14	0.09	3.80	0.00	0.00	0.12	0.12	1.28	2.85	3.67	4.66
0.20	3.11	0.15	4.02	0.00	0.08	0.19	0.15	1.52	2.98	4.01	4.77
0.25	4.24	0.01	6.00	0.00	0.00	0.00	0.02	2.39	4.36	5.91	7.24

Table J.3: OPTL, UPTL, RPTL, UxPTL and RxPTL under Changing DL, DLV, PTV and PUO, When BUS Is Active

DL	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.75	0.16	0.06	0.16	0.09	0.02	0.01	0.14	0.09	0.11	0.16	0.19
0.80	1.22	1.47	1.20	1.33	1.20	1.15	2.05	0.80	1.24	1.26	1.14
0.85	1.40	2.42	1.33	2.10	1.69	2.08	3.27	0.51	1.07	1.37	1.48
0.90	0.88	1.95	0.81	1.18	1.50	1.70	2.58	0.19	0.48	0.82	1.03
0.95	1.30	2.86	1.19	1.75	1.72	2.47	4.10	0.31	0.78	1.21	1.45

DLV	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.10	1.40	2.42	1.33	2.10	1.69	2.08	3.27	0.51	1.07	1.37	1.48
0.35	1.40	2.38	1.34	1.74	1.66	2.06	3.23	0.47	1.09	1.39	1.47
0.60	1.48	2.47	1.42	2.57	1.70	2.10	3.35	0.57	1.18	1.45	1.55
0.85	1.60	2.64	1.53	1.49	1.91	2.24	3.65	0.64	1.30	1.62	1.61
1.00	1.68	2.74	1.61	2.09	1.95	2.40	3.67	0.64	1.35	1.70	1.69

PTV	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.10	1.40	2.42	1.33	2.10	1.69	2.08	3.27	0.51	1.07	1.37	1.48
0.20	1.68	2.76	1.61	2.76	2.00	2.34	3.70	0.62	1.36	1.68	1.72
0.30	2.22	3.45	2.14	2.65	2.57	2.87	4.74	1.08	1.96	2.20	2.24

PUO	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.05	1.40	2.42	1.33	2.10	1.69	2.08	3.27	0.51	1.07	1.37	1.48
0.10	1.74	2.69	1.61	2.06	1.89	2.47	3.48	0.72	1.39	1.70	1.69
0.15	2.23	3.06	2.04	2.21	2.37	2.72	3.94	1.02	1.72	2.15	2.16
0.20	2.72	3.46	2.50	2.81	2.74	3.13	4.35	1.39	2.23	2.62	2.55
0.25	1.92	2.71	1.59	1.48	1.99	2.54	3.42	0.61	1.24	1.63	1.78

J.5 Tabulated Main Performance Measures When TAL Is Active

Table J.4: OPA, UPA, RPA, UxPA and RxPA under Changing DL, DLV, PTV and PUO, When TAL Is Active

DL	OPA	UPA	RPA	U1PA	U2PA	U3PA	U4PA	R1PA	R2PA	R3PA	R4PA
0.75	98.99	95.99	99.19	95.40	96.42	95.99	95.81	98.68	98.76	99.20	99.45
0.80	97.10	93.70	97.32	91.61	94.59	93.75	93.34	95.27	95.26	97.51	98.32
0.85	92.68	69.28	94.22	66.18	68.86	68.23	71.12	89.88	90.14	94.68	96.15
0.90	87.72	58.93	89.62	59.79	59.10	59.92	57.48	86.24	86.33	89.91	91.26
0.95	83.35	87.61	83.07	84.44	89.10	88.66	85.62	80.33	79.72	83.14	84.97
DLV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	92.68	69.28	94.22	66.18	68.86	68.23	71.12	89.88	90.14	94.68	96.15
0.35	92.23	67.88	93.84	69.95	66.00	67.31	69.48	89.61	89.65	94.34	95.74
0.60	91.53	65.30	93.25	67.29	64.15	65.27	65.79	89.64	89.71	93.56	95.02
0.85	90.47	64.93	92.15	59.97	67.87	64.86	63.82	89.40	89.52	92.35	93.51
1.00	89.63	66.65	91.15	58.47	69.69	66.92	65.31	88.78	88.81	91.36	92.29
PTV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	92.68	69.28	94.22	66.18	68.86	68.23	71.12	89.88	90.14	94.68	96.15
0.20	92.08	68.39	93.63	69.00	69.69	69.32	66.41	90.54	90.38	93.91	95.24
0.30	90.76	64.75	92.48	66.18	65.84	64.27	64.71	90.43	88.92	92.65	94.31
PUO	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.05	92.68	69.28	94.22	66.18	68.86	68.23	71.12	89.88	90.14	94.68	96.15
0.10	92.17	92.11	92.18	87.92	93.38	92.41	91.33	87.32	87.32	92.62	94.55
0.15	91.88	87.25	92.89	84.57	87.20	87.88	86.65	89.53	88.66	93.16	95.03
0.20	91.54	95.42	90.34	90.21	96.06	96.03	94.64	87.32	85.92	90.53	92.68
0.25	91.29	95.64	89.48	91.50	96.09	96.16	95.03	88.02	85.76	89.67	91.33

Table J.5: OPRL, UPRL, RPRL, UxPRL and RxPRL under Changing DL, DLV, PTV and PUO, When TAL Is Active

DL	OPRL	UPRL	RPRL	U1PRL	U2PRL	U3PRL	U4PRL	R1PRL	R2PRL	R3PRL	R4PRL
0.75	0.21	3.45	0.00	4.44	3.23	3.50	3.41	0.00	0.00	0.00	0.00
0.80	0.28	4.52	0.00	4.54	3.82	4.81	4.51	0.00	0.01	0.00	0.01
0.85	2.96	29.01	1.25	32.75	29.53	30.28	26.78	1.09	1.18	1.29	1.25
0.90	8.25	39.33	6.19	37.24	39.30	38.55	40.54	5.83	5.74	6.31	6.30
0.95	13.12	9.64	13.35	10.23	8.23	9.12	11.08	13.44	13.65	13.56	12.92
DLV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	2.96	29.01	1.25	32.75	29.53	30.28	26.78	1.09	1.18	1.29	1.25
0.35	3.32	30.41	1.53	28.19	32.50	31.32	28.28	1.43	1.59	1.52	1.53
0.60	4.38	33.24	2.48	31.19	34.53	33.43	32.45	2.70	2.34	2.56	2.43
0.85	6.11	33.62	4.30	39.32	30.94	33.95	34.17	4.31	4.48	4.23	4.29
1.00	7.31	31.97	5.68	38.64	29.24	31.98	32.91	5.39	5.63	5.66	5.75
PTV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	2.96	29.01	1.25	32.75	29.53	30.28	26.78	1.09	1.18	1.29	1.25
0.20	3.95	29.83	2.25	29.56	28.96	29.20	31.15	2.43	2.21	2.29	2.20
0.30	4.77	33.17	2.90	32.25	32.62	34.02	32.41	2.39	2.91	3.02	2.78
PUO	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.05	2.96	29.01	1.25	32.75	29.53	30.28	26.78	1.09	1.18	1.29	1.25
0.10	2.34	4.09	2.09	3.67	3.20	4.43	4.17	2.10	2.16	2.02	2.16
0.15	3.09	9.32	1.74	9.18	9.65	9.19	9.31	1.53	1.67	1.73	1.79
0.20	2.88	0.24	3.69	0.08	0.26	0.21	0.29	3.73	3.74	3.72	3.62
0.25	3.44	0.00	4.87	0.00	0.00	0.00	0.00	4.83	4.95	4.77	4.95

Table J.6: OPTL, UPTL, RPTL, UxPTL and RxPTL under Changing DL, DLV, PTV and PUO, When TAL Is Active

DL	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.75	0.80	0.56	0.81	0.16	0.35	0.50	0.17	1.34	1.24	0.80	0.55
0.80	2.62	1.78	2.68	3.85	1.59	1.44	4.20	4.96	4.73	2.49	1.67
0.85	4.35	1.71	4.53	1.07	1.60	1.50	1.62	10.04	8.68	4.04	2.61
0.90	4.04	1.74	4.19	2.97	1.60	1.53	4.96	9.19	7.92	3.78	2.44
0.95	3.53	2.75	3.58	5.33	2.67	2.22	6.31	7.75	6.63	3.30	2.12
DLV	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.10	4.35	1.71	4.53	1.07	1.60	1.50	1.62	10.04	8.68	4.04	2.61
0.35	4.45	1.71	4.63	1.86	1.51	1.37	2.66	10.00	8.75	4.14	2.73
0.60	4.09	1.46	4.27	1.52	1.32	1.30	2.26	8.55	7.95	3.88	2.55
0.85	3.42	1.46	3.55	0.72	1.20	1.19	1.20	7.04	6.01	3.42	2.20
1.00	3.06	1.37	3.17	2.89	1.07	1.10	4.94	6.57	5.56	2.97	1.96
PTV	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.10	4.35	1.71	4.53	1.07	1.60	1.50	1.62	10.04	8.68	4.04	2.61
0.20	3.98	1.78	4.12	1.44	1.35	1.48	2.08	7.77	7.41	3.80	2.56
0.30	4.47	2.08	4.62	1.57	1.53	1.72	2.37	7.95	8.17	4.33	2.92
PUO	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.05	4.35	1.71	4.53	1.07	1.60	1.50	1.62	10.04	8.68	4.04	2.61
0.10	5.49	3.80	5.73	8.41	3.41	3.17	9.56	12.12	10.53	5.36	3.29
0.15	5.03	3.43	5.38	6.26	3.15	2.93	7.40	9.99	9.67	5.11	3.18
0.20	5.58	4.34	5.97	9.71	3.68	3.76	10.77	10.25	10.35	5.75	3.70
0.25	5.27	4.36	5.65	8.50	3.91	3.84	9.29	8.13	9.29	5.57	3.72

J.6 Tabulated Main Performance Measures When SIMUL Is Active

Table J.7: OPA, UPA, RPA, UxPA and RxPA under Changing DL, DLV, PTV and PUO, When SIMUL Is Active

DL	OPA	UPA	RPA	U1PA	U2PA	U3PA	U4PA	R1PA	R2PA	R3PA	R4PA
0.75	98.85	95.44	99.07	99.78	95.83	95.14	95.37	98.89	98.92	99.09	99.13
0.80	97.20	80.53	95.02	89.46	81.92	82.44	76.74	94.95	93.71	95.11	95.61
0.85	94.91	78.48	94.17	86.85	82.83	79.39	74.77	94.75	93.15	94.27	94.54
0.90	91.35	82.08	94.52	86.89	86.82	83.81	77.34	94.79	94.26	94.62	94.52
0.95	87.82	80.53	94.06	86.22	83.46	82.64	75.99	93.73	94.85	94.55	93.06
DLV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	94.91	84.55	95.57	89.31	90.91	84.44	81.68	95.65	94.97	95.58	95.88
0.35	94.16	67.88	93.84	69.95	66.00	67.31	69.48	89.61	89.65	94.34	95.74
0.60	93.24	65.30	93.25	67.29	64.15	65.27	65.79	89.64	89.71	93.56	95.02
0.85	93.78	64.93	92.15	59.97	67.87	64.86	63.82	89.40	89.52	92.35	93.51
1.00	93.25	66.65	91.15	58.47	69.69	66.92	65.31	88.78	88.81	91.36	92.29
PTV	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.10	94.91	84.55	95.57	89.31	90.91	84.44	81.68	95.65	94.97	95.58	95.88
0.20	94.21	80.71	95.07	91.44	81.01	80.74	79.85	95.35	93.95	95.33	95.34
0.30	93.05	76.63	94.09	86.61	81.28	77.59	72.68	94.85	93.44	94.28	94.14
PUO	**OPA**	**UPA**	**RPA**	**U1PA**	**U2PA**	**U3PA**	**U4PA**	**R1PA**	**R2PA**	**R3PA**	**R4PA**
0.05	94.91	84.55	95.57	89.31	90.91	84.44	81.68	95.65	94.97	95.58	95.88
0.10	94.53	82.05	96.25	87.65	84.82	82.94	79.37	96.56	95.84	96.34	96.32
0.15	94.22	83.94	96.46	91.44	86.81	83.54	82.55	96.26	95.95	96.48	96.72
0.20	93.99	84.93	96.77	91.86	85.49	85.57	83.39	96.29	96.18	96.93	96.91
0.25	92.91	84.56	96.31	93.18	86.64	85.18	82.13	95.74	96.72	96.48	95.93

Table J.8: OPRL, UPRL, RPRL, UxPRL and RxPRL under Changing DL, DLV, PTV and PUO, When SIMUL Is Active

DL	OPRL	UPRL	RPRL	U1PRL	U2PRL	U3PRL	U4PRL	R1PRL	R2PRL	R3PRL	R4PRL
0.75	0.63	4.11	0.41	0.00	3.81	4.57	3.92	0.53	0.59	0.36	0.36
0.80	3.13	18.22	2.17	10.45	17.70	16.44	21.39	2.93	2.58	2.07	2.02
0.85	4.08	20.40	3.05	13.06	16.48	19.59	23.70	2.41	3.33	3.04	2.97
0.90	4.32	17.29	3.49	12.64	12.78	15.77	21.64	3.93	3.61	3.35	3.58
0.95	5.20	18.75	4.34	13.41	16.48	16.75	22.81	5.20	3.55	3.84	5.31
DLV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	2.82	14.35	2.09	10.45	8.41	14.63	16.76	1.95	2.25	2.14	1.95
0.35	3.32	30.41	1.53	28.19	32.50	31.32	28.28	1.43	1.59	1.52	1.53
0.60	4.38	33.24	2.48	31.19	34.53	33.43	32.45	2.70	2.34	2.56	2.43
0.85	6.11	33.62	4.30	39.32	30.94	33.95	34.17	4.31	4.48	4.23	4.29
1.00	7.31	31.97	5.68	38.64	29.24	31.98	32.91	5.39	5.63	5.66	5.75
PTV	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.10	2.82	14.35	2.09	10.45	8.41	14.63	16.76	1.95	2.25	2.14	1.95
0.20	3.30	18.04	2.36	7.84	18.61	18.43	17.92	2.62	2.89	2.08	2.41
0.30	3.94	21.69	2.82	13.06	17.26	21.18	24.86	3.10	2.90	2.69	2.91
PUO	**OPRL**	**UPRL**	**RPRL**	**U1PRL**	**U2PRL**	**U3PRL**	**U4PRL**	**R1PRL**	**R2PRL**	**R3PRL**	**R4PRL**
0.05	2.82	14.35	2.09	10.45	8.41	14.63	16.76	1.95	2.25	2.14	1.95
0.10	3.45	16.76	1.62	12.30	14.26	16.03	19.07	1.62	1.66	1.55	1.69
0.15	4.06	14.90	1.71	8.31	12.47	15.35	15.96	2.31	1.99	1.69	1.53
0.20	4.74	14.12	1.87	7.50	13.81	13.72	15.22	2.89	2.51	1.70	1.66
0.25	6.49	15.00	3.03	6.64	13.09	14.47	17.21	3.97	2.76	2.88	3.30

Table J.9: OPTL, UPTL, RPTL, UxPTL and RxPTL under Changing DL, DLV, PTV and PUO, When SIMUL Is Active

DL	OPTL	UPTL	RPTL	U1PTL	U2PTL	U3PTL	U4PTL	R1PTL	R2PTL	R3PTL	R4PTL
0.75	0.52	0.44	0.52	0.22	0.35	0.29	0.71	0.58	0.49	0.55	0.51
0.80	2.72	1.25	2.81	0.10	0.38	1.12	1.87	2.12	3.71	2.97	2.37
0.85	2.68	1.13	2.78	0.09	0.69	1.03	1.53	2.83	3.52	2.85	2.49
0.90	1.90	0.63	1.99	0.46	0.40	0.42	1.03	1.28	2.13	2.15	1.90
0.95	1.55	0.73	1.60	0.37	0.06	0.61	1.20	1.07	1.60	1.71	1.63
DLV	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.10	2.27	1.10	2.34	0.24	0.69	0.94	1.56	2.40	2.78	2.39	2.17
0.35	4.45	1.71	4.63	1.86	1.51	1.37	2.66	10.00	8.75	4.14	2.73
0.60	4.09	1.46	4.27	1.52	1.32	1.30	2.26	8.55	7.95	3.88	2.55
0.85	3.42	1.46	3.55	0.72	1.20	1.19	1.20	7.04	6.01	3.42	2.20
1.00	3.06	1.37	3.17	2.89	1.07	1.10	4.94	6.57	5.56	2.97	1.96
PTV	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.10	2.27	1.10	2.34	0.24	0.69	0.94	1.56	2.40	2.78	2.39	2.17
0.20	2.49	1.25	2.56	0.73	0.38	0.83	2.23	2.03	3.17	2.72	2.25
0.30	3.01	1.68	3.09	0.33	1.46	1.24	2.47	2.06	3.66	3.21	2.95
PUO	**OPTL**	**UPTL**	**RPTL**	**U1PTL**	**U2PTL**	**U3PTL**	**U4PTL**	**R1PTL**	**R2PTL**	**R3PTL**	**R4PTL**
0.05	2.27	1.10	2.34	0.24	0.69	0.94	1.56	2.40	2.78	2.39	2.17
0.10	2.01	1.18	2.13	0.05	0.92	1.03	1.56	1.82	2.50	2.18	1.98
0.15	1.71	1.16	1.84	0.26	0.73	1.11	1.50	1.42	2.06	1.89	1.76
0.20	1.27	0.95	1.37	0.65	0.70	0.71	1.39	0.83	1.31	1.41	1.44
0.25	0.59	0.44	0.65	0.17	0.27	0.35	0.66	0.29	0.52	0.66	0.77

Appendix K

Plots for the TAL Accept/Reject Rule

In this appendix the plots of the exploratory experiments involving the control limits of the accept/reject rules have been provided. These were referred in Chapter 5 (section 5.1.2).

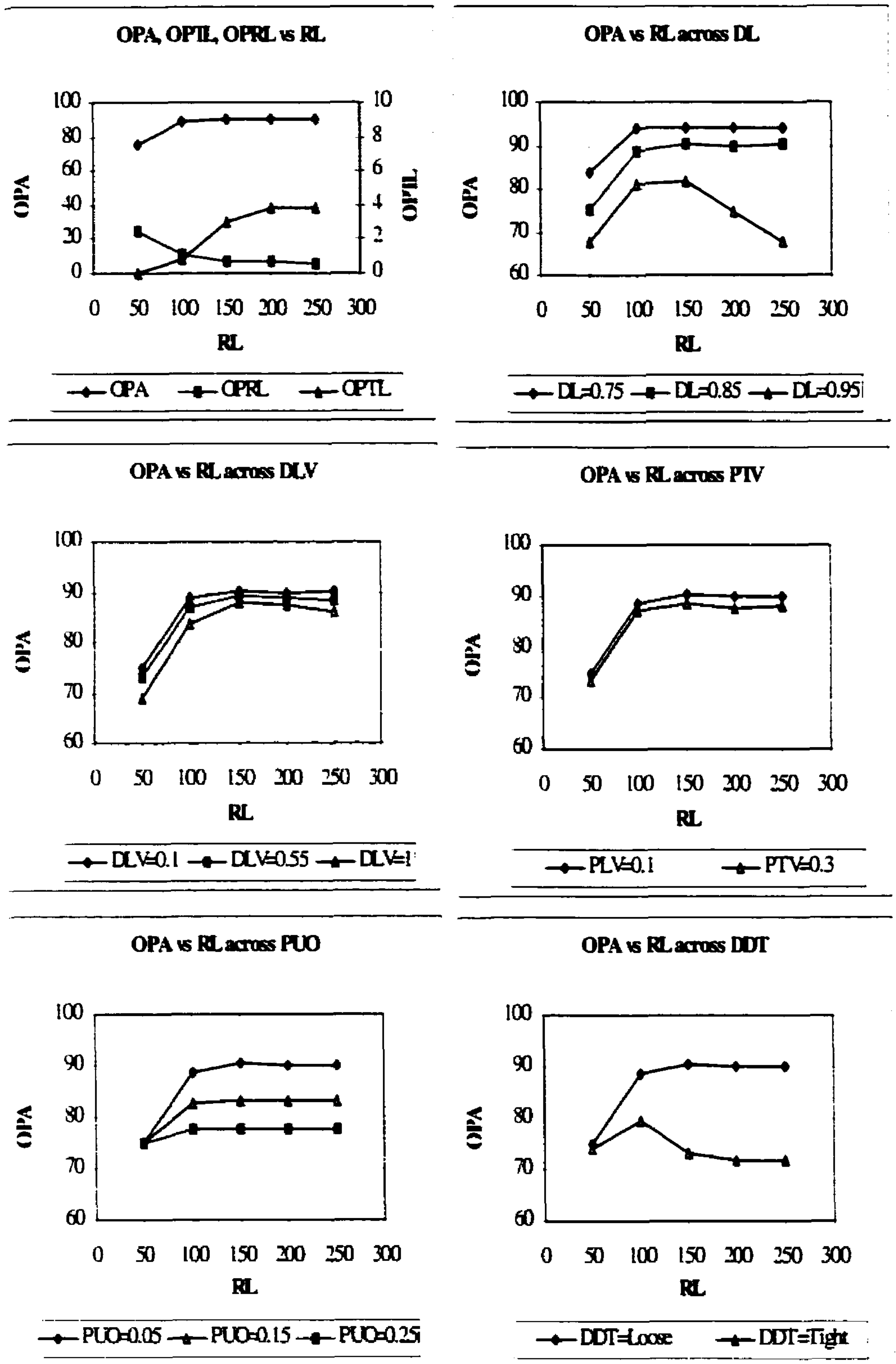

Figure K.1: Plots for the TAL Accept/Reject Rule