A Simulated Based Approach to Develop New Approaches for “Due Date Assignment” and “Job Release” in Multi-Stage Job Shops

PhD Thesis

In

Industrial Engineering

University of Gaziantep

Supervisor

Prof.Dr. Adil BAYKASOĞLU

by

Mustafa GÖÇKEN

February 2009

T.C.
UNIVERSITY OF GAZİANTEP
GRADUATE SCHOOL OF
NATURAL & APPLIED SCIENCES
INDUSTRIAL ENGINEERING

Name of the thesis: Integrating Data Mining and Discrete Event Simulation for Analyzing Production Systems
Name of the student: Mustafa GÖÇKEN
Exam date: 27.02.2009

Approval of the Graduate School of Natural and Applied Sciences

Prof.Dr. Ramazan KOÇ
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy.

Prof.Dr. Adil BAYKASOĞLU
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Doctor of Philosophy.

Prof.Dr. Adil BAYKASOĞLU
Supervisor

Examining Committee Members	Signature
Prof. Dr. İ. Burhan TÜRKŞEN	________________
Prof. Dr. İ. Hüseyin FİLİZ	________________
Prof. Dr. Rızvan EROL	________________
Prof. Dr. Türkay DERELİ	________________
Prof. Dr. Adil BAYKASOĞLU	________________

ABSTRACT

A SIMULATED BASED APPROACH to DEVELOP NEW APPROACHES for "DUE DATE ASSIGNMENT" and "JOB RELEASE" in MULTI-STAGE JOB SHOPS

GÖÇKEN, Mustafa
PhD in industrial eng.
Supervisor: Prof. Dr. Adil BAYKASOĞLU

Feb 2009, 284 pages

Workload control (WLC) concepts are advocated as one of the new production planning and control (PPC) methods. In its elaborated form, WLC includes three major decision levels: (i) job entry, (ii) job release, (iii) priority dispatching. In each decision levels, several decision points which have significant impact on the effectiveness of the PPC are defined (i.e. acceptance/rejection, due date assingment etc.). In order to improve the effectiveness of PPC, WLC systems should consider all these decision points simultaneously. In adddition to these decision points, flexibility of the shop can be included as the fifth decision point which allows the shop capacity to be adjusted as new orders enters the system and as they are released to the shop floor.

In this study, simulation models which enable the effect of each decision points within this WLC concept to be explored are developed and tested. The results revealed that simultaneous consideration of decision points improves the effectiveness of PPC. Moreover, a composite dispatching rule which can be used in priority dispatching level to improve the effectiveness of other levels is developed by using a data mining tool.

Keywords: production planning and control, workload control, simulation, data mining

ÖZET

ÇOK AŞAMALI ATÖLYE TİPİ ÜRETİM SİSTEMLERİNDE “TESLİM TARİHİ ATAMA” VE “SİPARİŞ SALMA” İÇİN BENZETİM TABANLI YENİ YAKLAŞIMLAR

GÖÇKEN, Mustafa
Doktora Tezi, Endüstri Mühendisliği
Tez Yöneticisi, Adil BAYKASOĞLU

Şubat 2009, 284 sayfa

İş yükü kontrol (İYK) kavramları yeni üretim planlama ve kontrol (ÜPK) yöntemleri arasında sayılmaktadır. İYK’nın gelişmiş hali, (i) iş giriş, (ii) iş salma ve (iii) öncelikli yönlendirme olmak üzere üç önemli karar aşamasını içermektedir. Her bir karar aşamasında ÜPK’nın etkinliğine önemli ölçüde etkisi olan karar noktaları tanımlanmaktadır (kabul/ret, teslim tarihi atama vb). İYK sistemleri, ÜPK’nın etkinliğini artırmak amacıyla tüm karar noktalarını eşzamanlı dikkate almalıdır. Bu karar noktalarına ek olarak, bu çalışmada yeni siparişler atölyeye geldiğinde ve atölyeye salındığında kapasite ayarlamaya imkân veren atölye esnekliği de beşinci bir karar noktası olarak düşünülmüş ve diğer karar noktalarının dolayısıyla ÜPK’nın etkinliğine etkisi incelenmiştir.

Bu çalışmada, İYK kavramı içerisinde yer alan her bir karar noktasının etkisinin araştırılmasına olanak sağlayan benzetim modelleri geliştirilmiş ve test edilmiştir. Benzetim deneylerinin sonuçları, beş karar noktasının eşzamanlı düşünülmesinin ÜPK’nın etkinliğini artırdığını göstermiştir. Ayrıca, gelişmiş bir veri madenciliği aracı kullanılarak öncelikli yönlendirme aşamasında kullanılabilecek ve diğer karar aşamalarının etkinliğini artırmaya yardımcı olabilecek bir karma yönlendirme kuralı geliştirilmiştir.

Anahtar kelimeler: üretim planlama ve kontrol, iş yükü kontrol, benzetim, veri madenciliği

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my supervisor, Prof. Dr. Adil BAYKASOĞLU for his encouragement, guidance, suggestions and help during the study.

I am very grateful to Prof. Dr. İ. Burhan TÜRKŞEN, Prof. Dr. Hüseyin FİLİZ, Prof. Dr. Türkay DERELİ and Prof. Dr. Rızvan EROL for their valuable criticisms.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS/ABREVIATIONS

ADRES	Adaptive rate exponential rate smoothing
AE	Average earliness
AGGWNQ	Aggregate workload trigger, work-in-next-queue selection
ANOVA	Analysis of variance
APWT	Average pre-shop pool waiting time
AQWT	Average total queue waiting time
AT	Average tardiness
BUFSIZ	Buffer size
CDDAM	Conventional due date assignment models
DDAM	Due date assignment model
DDTight	Due date tightness
DF	Degree of flexibility
DPPW	Dynamic process plus waiting time
DR	Dispatching rule
DTWK	Dynamic total work content
EDD	Earliest order due date
E (%)	Proportion of early jobs
F_{avg}	Average total flowtime
FCFS	First come first served
IMR	Immediate Release
IntArr	Interarrival time
I/OC	Input/output control
İYK	İşyükü kontrol
LDP	Last data point
M	Makespan
MAPE	Mean absolute percent error
MEPAR-miner	Multi-expression programming for classification rule mining
MEP	Multi-Expression Programming
MLT	Manufacturing lead time
MPE	Mean percent error
MT	Mean tardiness
MTO	Make-to-order
MTS	Make-to-stock
OR	Order release
ORR	Order/review release
PDDAM	Proposed due date assignment models
PPC	Production planning and control
PPW	Process plus waiting time
Prl	Pool release length
PSP	Pre-shop pool
R	Total number of rejected orders

SDEPQ	Search dept of queue
SFC	Shop floor control
SFTT	Shop floor throughput time
SPT	Shortest processing time
STD. L	Standard deviation of lateness
S/OPN	Slack per remaining operation
$\mathbf{T_{avg}}$	Average tardiness
TWK	Total work content
T (%)	Proportion of tardy jobs
ÜPK	Üretim planlama ve kontrol
WCEDD	Work center workload trigger, earliest due date selection
WC	Workcenter
WIP	Work-in-process
WLC	Workload control
WLL	Workload level

CHAPTER 1

INTRODUCTION

1.1. Theoretical Background

Production planning and control (PPC) systems are crucial to help meet increasingly high customer demands and expectations as markets become more competitive in the present manufacturing climate. Typical functions of a PPC system include planning material requirements, input and output control (I/OC), and the scheduling and sequencing of jobs (see, for example, Zapfel and Missbauer, 1993) (Stevenson M. and Hendry L, 2006). Among these, I/OC which is advocated as input regulation, order/review release (ORR), workload control (WLC) has been attracting increasing attention since 1980s. WLC has been elaborated in the early 1980s to a hierarchical production control concept for job shop manufacturing (Breithaupt et al., 2002). Nowadays, WLC concepts are known to be a new group of production planning and control methods (Hendry et al, 1998). The main idea behind the WLC concepts is to buffer the shop floor against external dynamics by creating a pool of unreleased jobs (Land and Gaalman, 1996).

Many managers and researchers of the literature on the production planning problems of job shop environments have focused on the dispatching process. In almost all of these studies and practices, the main focus was on scheduling jobs through each work center. Melnyk et al. (1989) stated that in many of the shop floor control (SFC) studies (e.g. Convey et al., (1967), the focus was not controlling the rate at which jobs entered the shop (this was assumed to be outside the control of the shop floor), but rather on dispatching. They cited Eilon et al. (1975) for supporting this argument: “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”.

Dispatching rules (DR) are often favored because of their simplicity, ease of application and the fact that they are an on-line scheduling method that can be used in real-time scheduling. This makes them dynamic in the sense that they can process new job arrivals and react to other disruptions without the need to re-schedule (Al-Turki et al., 2004). However, DRs' main disadvantage is that they can not adapt themselves to changing system statuses (i.e. peaks and valleys of the work loads in front of the work centers) which causes to deteriorate their performance, under different levels of the system congestions, for which they have been developed (Baykasoğlu et al., 2007). Their disadvantage is emphasized in many studies where it is concluded that dispatching rules have been classified mainly according to the performance criteria for which they have been developed. Due to being problem dependent, many sophisticated dispatching rules or a combination of them were developed to get improved shop floor performance at all possible levels of shop congestion. In fact, most of them provide relatively improved shop floor performance but it is outweighed by the solution complexity which makes them essentially impractical. As a result, simple, practical, and problem independent dispatching rule have not been developed yet. Such drawbacks of dispatching rules deteriorate effectiveness of the SFC. This is mainly because of neglecting vital function of SFC, ORR.

One of the first through examinations or the ORR function was undertaken by Harty (1969) who placed great emphasis on the relationship ORR and the control of production capacity (Melnyk and Ragatz, 1988). Harty (1969) argued that ORR affects capacity requirements by governing the rate of input into the production system and noted that the secret to capacity control is not releasing work. Wight (1970) refers to ORR by a different point of view. According to him, in order to obtain fairly constant lead times at each work center, the levels of work-in-process (WIP) at each work center should remain relatively constant. It is emphasized that stabilizing WIP at a relatively constant levels can only be achieved by controlling the flow of work both to the shop (i.e. by ORR function) and within the shop. Actually, the performance of the shop floor could be improved only by this way. During the last four decades, Wight's (1970) I/OC concept has been elaborated. Since then I/OC has been extended to a class of hierarchical capacity oriented production control concepts for job shops (Land and Gaalman, 1996). There have been several well-developed WLC concepts presented in the literature that address two major decision levels in make-to-order (MTO) (i.e., particularly those characterized by job shop production) firms, the job entry level and the job release level (Hendry et al., 1998).

The bulk of the literature on WLC concept assumed that all incoming orders regardless of shop condition are accepted. In this respect, the control of the shop floor is only maintained by job release level. However, it is recognized that workload control can be made earlier, at the job entry level. Because, the main aim of the workload control is not to control the lengths of the queues in front of work centers on the shop floor but is to meet the promised due dates with the resources available. Thus, job release stage can itself only be fully effective if the queue of jobs in the pool is also controlled. This means acceptance of orders to planning system (i.e., PSP) must be restricted by allowing a maximum number of orders or workload to be placed in PSP. Otherwise jobs remain in the pool for too long so missing their promised due dates (Kingsman, 2000). In this respect, the job entry level and the job release stage should be considered interdependent. As Land and Gaalman (1996) noted, the control of workload on the shop floor creates a backlog/pool of orders waiting for release. The pool is claimed to buffer the shop floor against external dynamics. Then, PSP can be considered as a filter to the manufacturing system and also a triggering mechanism whether to accept or reject incoming jobs.

As mentioned above, in well-developed WLC concepts there are two major decision levels. At the first decision level (i.e., customer enquiry) there exist two major decision points i.e., called acceptance/rejection and due date assignment. Acceptance/rejection of incoming orders is an important decision point in the customer enquiry level which provides input control and adjusts midterm capacity (i.e., output control). Another important decision point at customer enquiry level is due date assignment which is one of the most critical elements in production control. In scheduling literature, numerous studies exists related to due date assignment. The bulk of the literature aimed at developing a due date assignment rule which reacts to dynamically changing systems. Main measures of due date assignment rules' performances are defined to be delivery reliability and delivery speed. Delivery reliability deals with the magnitude of errors between realized and assigned job completion times. Delivery speed deals with the length of the flow allowance. Due date information is significant input for the manufacturing management system of the vendors since it serves as a basis for the production planning and control system as well as for issuing orders to subcontractors, suppliers of raw material and other exogenous agents (Smith and Seidman, 1983). In terms of WLC concept, due date information of incoming orders is crucial to output control and utilized whenever adjusting medium term capacity. Thus, a sophisticated due date assignment rule must be used in order to improve the effectiveness of WLC concept.

At the second decision level (i.e. job release) there exists only one decision point called i.e., job release. Job release decisions are made regarding which jobs should be released to the shop floor. The jobs are released to the shop floor according to the logic of order release mechanism (OR mechanism). While many OR mechanisms that have different logic proposed in the literature they all aimed at adjusting short term capacity. Melnyk et al. (1991) argued that the combination of job entry level and job release stage diminishes the performance advantage the sophisticated DRs over the simpler DRs. This suggests that careful use of filtering mechanisms in both job entry and job release stages can allow the use of much simpler DRs for control of jobs once they are released to the shop floor. In spite of this fact, dispatching process can be included as a third decision level to the hierarchical WLC concept to explore its main and interaction effects on shop floor control. Moreover, Land and Gaalman (1996), Kingsman et al. (1989), Kingsman (2000) are some of the researchers who already considered dispatching process as a third decision level in their hierarchical WLC concepts.

1.2. Motivation of the Study

In 60s and 70s, job shop studies largely concerned with the experimental evaluation of DRs. In those days, it is believed that the only control parameter at the disposal of the scheduler is only DR. In late seventies, it is reported by researchers (e.g., Eilon and Chowdhury (1976), Weeks and Fryer (1977)) that the performance of the shop is controlled by a combination of DR and due date assignment models. Then, much more research study investigated these two control parameters and their interactions on shop performance. Meanwhile, in early seventies several studies (e.g., Harty (1969), Wight (1970), and Nicholson and Pullen (1972)) concerning the theoretical benefits of ORR and/or current practices in ORR were published. These works are respected as seminal works related to ORR within the context of SFC systems. In eighties many experimental works that incorporates OR mechanisms were conducted whether it improves the performance of the shop or not. But, ORR still found to be at the center of a controversy (i.e., whether it plays a critical role or not in the operation of SFC). Melnyk and Ragatz (1989) have tried to resolve this controversy by developing and presenting several paradigms for the study of ORR mechanism. But, their success found to be limited. Later, Melnyk et al. (1991) call attention to planning system (i.e., customer enquiry) which affects the operation of ORR system and the subsequent performance of the shop. To these authors, many research studies investigating the impact of ORR mechanisms ignore the possibility that the manufacturing planning system may be managing the incoming work flow so that peaks and valleys in the workload have been smoothed out. They found that the combination of smoothing by planning system with ORR results in shorter and more consistent lead times, lower and more stable WIP levels, and better delivery performance. Since then, major part of the effectiveness of the ORR function attributed to management of the PSP. Philipoom and Fry (1992), relaxed a common assumption of the published literature on ORR that all orders received by the shop will be accepted, regardless of shop conditions by enabling rejection of incoming orders in times of high shop congestion. This study dictates that acceptance/rejection decisions must be made to improve the effectiveness of the SFC at customer enquiry stage.

All these studies constitute the basis of WLC concept. WLC concept is elaborated by many valuable research studies (e.g., Kingsman, et al. 1989). In its hierarchical form, WLC concept incorporates three decision levels and some decision points in each decision level. Nowadays, contrary to past studies these decision points are thought to be at the disposal of SFC manager.

In this thesis, each decision points at each decision level mentioned above and their interactions on shop performance are investigated. Land and Gaalman (1996) call attention to the importance of keeping the PSP size at a certain level. By this way the whole shop can be protected against external dynamics. They also noted that, the whole shop can also be protected against external dynamics via high flexibility of the capacity. In this study, apart from the published literature on ORR, the effect of stationary PSP size as well as flexibility of the capacity on the effectiveness of the ORR are considered together.

1.3. Objectives of the Study

In the previous section, the objectives of the study are given implicitly. More specifically, the objectives of the study are given as follows:

1. To develop a dynamic due date assignment rule that reacts to dynamically changing system conditions.
2. To gain insight into the basic operation of hierarchical WLC concept. To do this, a hierarchical WLC concept developed with its three major decision levels (i.e., customer enquiry, job release, and dispatching levels) and decision points at each level (i.e., acceptance/rejection rule and due date assignment at the customer enquiry level, OR mechanisms at the job release level, and DRs at dispatching level).
3. To investigate the optimal choice of the load level of OR mechanisms considered in the study according to main measures of shop performance. Note that, while determining optimal load level of each OR mechanism other factors are taken into account.
4. To explore the main and interaction effects of decision points on shop performance. To do this, different levels of decision points are determined and their combinations are tested with computer simulation. The results of these simulation runs are analyzed statistically to observe: a. Whether the main effects of decision points are statistically significant on shop performance, b. Whether the interaction effects of decision points are statistically significant on shop performance.
5. To observe behavior of ORR function under simultaneous usage of input and output control. To do this, certain levels of PSP size is tested along with certain levels of capacity flexibilities (i.e., output control).
6. To develop a composite DR that reacts to dynamically changing system condition by a talented data mining technique.

1.4. Organization of the Thesis

The rest of the thesis is arranged in the following way. In chapter 2, two dynamic due date assignment model (DDAM) is proposed and compared with its sophisticated counterparts from the literature. A comprehensive literature review, the methodology, results and conclusions are included in chapter 2. In chapter 3, a framework of ORR is introduced and a detailed literature review in the area of ORR (i.e., WLC) is reported. The methodology, experimental strategy, experimental factors, experimental designs and results are all included in chapter 3. Chapter 3 ends with a comprehensive conclusion. In chapter 4, composite dispatching rules are developed by using a sophisticated data mining tool. In chapter 5, concluding remarks and directions for further studies is given.

CHAPTER 2

DUE DATE ASSIGNMENT

In this chapter, two new approaches for due date assignment in job shops are evaluated. Proposed approaches use statistical prediction techniques for dynamic prediction of job flowtimes in a job shop environment as the job arrives to the shop floor. Primary objective of this research is to compare the performance of the proposed due date assignment model (*PDDAM*) with several conventional due date assignment models (*CDDAM*). For this purpose, simulation models are developed and comparisons of the *PDDAM* and *CDDAM* are made in terms of the mean absolute percent error (*MAPE*), mean percent error (*MPE*) and mean tardiness (*MT*).

2.1 Introduction

In job shop scheduling literature, estimation of job flowtimes has always been an important issue since late 1960s. Because the flowtime estimation is used to assign order due dates, the problem has been mostly studied within the context of due date assignment (Sabuncuoglu et al., 2000). The importance of meeting promised delivery dates, or due dates, in a job shop is recognized by practicing production managers and academic researchers (Ragartz, et al., 1984b).

The ability to meet due dates, however, is dependent not only on the scheduling dispatching procedure followed, but also on the reasonableness of the due dates (Ragartz et al*.,* 1984b). The reasonableness of the due dates can be measured simply by some due date performances. Because product or service delivery systems are not necessarily capable of successfully achieving an arbitrary set of due dates, the reasonableness of assigned due dates directly affects due date performance (Vig et al., 1991). There are two aspects of due date performance -delivery reliability and delivery speed (Hill, 1991). Delivery reliability which is also referred to as missed due-date (Cheng et al., 1998) is the ability to consistently meet promised delivery

dates, delivery speed is the ability to deliver orders to the customer with shortest lead times (Philipoom, 2000). Recent trends in time based competition and inventory reduction requires products to be completed in shorter time and with more reliable delivery dates. At the operational level, this can be made possible via better scheduling and due date management. Theoretical model and statistical analysis highlight the importance of lead time variances in affecting quality, delivery reliability and time, productivity, and product flexibility. Naturally, due date reliability at micro level determines the stability of manufacturing lead times and consequently a firm's strategic competencies (Veral, 2001).
With the current emphasis on the just in time (*JIT*) production philosophy, it is crucial to meet the target due date (Sha et al., 2004). An early job completion results in inventory carrying costs, such as storage and insurance costs. On the other hand, a tardy job completion results in penalties, such as loss of customer goodwill and damaged reputation (Hino et al., 2005). Hence meeting due dates tends to be the primary concern of the most production managers (Melnyk et al., 1986) including those of the job shops, which usually have process layouts and are suitable for high variety, low volume, make to order production (Chang, 1997).

Due date performance is becoming increasingly important in today's volatile production environment. The current trend has been toward due date assignment investigations that concentrate on dynamic flowtime estimation models (Vig et al., 1991). In fact, the flowtime prediction problem is really the crux of the due date management problem. The due date assignment process consists of making an estimate of flowtime for a job and then setting a due date on the basis of that estimate and some performance criteria (Ragartz et al., 1984a).

In this study, flowtime estimation and due date assignment is achieved by using two proposed due date assignment models namely adaptive response rate exponential smoothing (*ADRES*) model and last data point (*LDP*) model and two conventional due date assignment models namely dynamic total work content (*DTWK*) model and dynamic process plus waiting (*DPPW*) model. Main objective of this research is to compare the performance of *PDDAM* with *CDDAM* with respect to selected performance criteria. Main reason for this comparison is to find the best due date assignment model (*DDAM*) that estimates the flowtime of orders accurately and precisely. The remainder of this chapter is organized as follows. In section two, literature review and information about research outline are given. Then, in section three, experimental design is outlined. In section four, simulation results are discussed and analyzed. In section five conclusions are given.

2.2 Literature Review and Research Outline

Early studies in the area of due date assignment (e.g., Conway, 1965; Eilon et al., 1967; Miyazaki, 1981; Baker, 1984b; Ragartz et al. 1984a, Cheng, 1988; Cheng et al., 1998; Chiu et al., 2003; Sha et al., 2004) were focused on only job related information. For example; the total work content (TWK) requires that each job has to be assigned an allowance that is a multiple of job processing time (e.g., Eilon et al., 1967; Ragartz et al., 1984;Cheng et al., 1998, Anderson et al., 1990; Chiu et al., 2003; Sha et al., 2004), another due date assignment rule number of operations (*NOP*) defined estimated flowtime of a job as a function of its number of operations to be performed (e.g., Ragartz et al., 1984; Chiu et al., 2003), equal slack (*SLK*) determines due date based on the common slack (q) which is added to the sum of the release dates and processing times of individual jobs (e.g., Baker et al., 1981; Baker et al., 1982), constant flow allowance (*CON*) gives equal allowance to each job (Cheng, 1987), process plus waiting (*PPW*), combines the *CON*, *SLK* and *TWK* into one model, in which the due dates are linear functions of the job's processing time (e.g. Cheng et al., 1998). Note that, these models use only job related information. For convenience, their formulas are given as follows:

$$
\begin{aligned}
&TWK: && d_i = r_i + kp_i \\
&NOP: && d_i = r_i + km_i \\
&SLK: && d_i = r_i + p_i + q \qquad\qquad i = 1, 2, 3, \ldots n \\
&PPW: && d_i = r_i + kp_i + q \\
&CON: && d_i = r_i + k
\end{aligned}
$$

Where r_i and p_i denote the arrival time for job i and processing time of job i respectively. The parameter k would be chosen differently for each rule in order to achieve a given average flow allowance, q is a slack allowance which may be negative, m_i, number of operations required to complete job i.

Following investigations aimed at developing more reasonable *DDAMs*. By this aim, researchers used shop related information together with job related information for assigning due dates. For example, jobs in queue (*JIQ*) (e.g. Ragartz et al., 1984a; Chiu et al., 2003), jobs in system (*JIS*) (e.g. Ragartz et al., 1984a), work in queue (*WIQ*) (e.g. Ragartz et al., 1984a) can be taken into account as some examples of these *DDAMs*.

In *JIQ* model; at the release time of job i to the shop, all work center queues on job i's routing are polled for the number of jobs in queue (JIQ_i). This shop status information is then combined with the total process time (p_i) to estimate job i's flowtime. In *WIQ* model; the total processing time of all jobs in the work center queues on job i's routing is utilized. *JIS* is incorporating the general congestion level of the shop rather than only the current congestion on job i's routing.

$$JIQ\text{: } FLOWi = k_1 p_i + k_2 (JIQ_i)$$
$$WIQ\text{: } FLOWi = k_1 p_i + k_2 (WIQ_i)$$
$$JIS\text{ : } FLOWi = k_1 p_i + k_2 (JIS_i)$$

In either *DDAMs* which use job related information or shop related information, more accurate and precise flowtime can be obtained only by using the most appropriate k. However, determination of the most appropriate k for all jobs and different system state is not so simple. To be able to overcome this problem, dynamic *DDAMs*, which update k for all jobs and different system state, have been developed in the literature. In fact, dynamic *DDAMs* have been developed by letting k dynamically updated. Up to date, various techniques among various disciplines for updating k dynamically have been investigated. For example, Vig et al. (1991) proposed two rules (Operation flowtime sampling (*OFS*), Congestions and operation flowtime sampling (*COFS*)), which estimate job flowtime, based on a sampling of recently completed jobs. These rules are compared with other established *DDAMs* (*JIQ*, *TWK* and *NOP*). Each of the *DDAMs* requires estimates for one or more parameters. In their study, Vig et al. (1991) employed multiple linear regression technique to obtain the best values for the parameters of each *DDAMs*. Enns (1993) employed CON_p, $DCON_p$, PPW_p, $DPPW_p$ *DDAMs* under conditions where Jackson's decomposition principle can be applied. The subscript "p" associated with each of these models indicated that the due date rule multipliers were being set to be consisted with predicted flowtimes. These *DDAMs* assign due date of jobs dynamically by using queue analysis. Enns (1995) developed three analytically derived *DDAMs*, which were called, dynamic forecasting model (*DFM*), jobs in system feedback model (*JFM*), and work in process feedback model (*WFM*). Cheng et al. (1998) proposed two *DDAMs* in order to improve the performance criteria based on missed due dates. Proposed *DDAMs*, which named dynamic *TWK* (*DTWK*) and dynamic *PPW* (*DPPW*), are analytically-derived. Sha et al. (2004) proposed rule based *TWK* (*RTWK*) that incorporated a data mining tool to be able to adjust an appropriate factor *k* according to the condition of the shop at the instant of job arrival. Raghu et al. (1995), proposed three different methodologies of setting the parameter coefficients for the due date setting rule. The methods were: A search algorithm, simulated annealing algorithm, and, a combination of simulated annealing algorithm and regression analysis. Chiu et al. (2003) suggested case based reasoning (*CBR*) for solving due date assignment problem since most production orders are similar to those previously manufactured. Proposed *CBR* approach employs the k-nearest neighbor's concept with dynamic future weights and non-linear similarity functions. Sha et al. (2004) developed artificial neural network (*ANN*) based *DDAMs* combined with simulation technology. Regression-based *DDAMs* were used as benchmarking.

In early researches, all these dynamic *DDAMs* were compared with their static counterparts and it was observed that dynamic *DDAMs* reduced due date prediction errors. Therefore, it is apparent that including static *DDAMs* in this study as benchmark is needless. Finally, in this study due dates of jobs are assigned by using two dynamic *PDDAMs* and two dynamic *CDDAMs* as benchmarking.

Primary objective of this research is to compare the performance of *PDDAM* with *CDDAM* with respect to selected performance measurements. Second objective of this study is to examine whether there is a relationship between due date assignment models, dispatching rules and shop load levels and evaluate the influence of these factors on the performance of due dates. The background information and the components of the present work are explained in the following sub-sections.

2.2.1. Flow time estimation in job shops

The time a job spends in the shop, from order release to completion is called its flowtime. The mean job flowtime is the basic measure of a shop's performance at turning around orders, and it is therefore often used as an indicator of success in responding quickly to customers (Baker, 1984a). In a job shop environment meeting due-dates on time and utilize existing capacity efficiently is a complex problem than in other production systems due to four reasons stated below:

- Too many kinds of orders can be received,
- Each order has its own route between the workstations, so that different routings may occur.
- Some equipments and materials can be used jointly between the work stations which may cause unavoidable delays.
- Different jobs could have different priorities.

As a result of complex structure of job shop, flowtime elements become uncertain which makes the accurate prediction of flowtime more difficult. However, accurate prediction of flowtime in job shop is one of the most important factors for the efficiency of scheduling. If flowtime predictions can be significantly improved through use of dynamic shop load information, costs related to deviations between actual completion times and promised delivery dates can be reduced (Enns, 1993). Flowtime of each job can be calculated by using Eq. (2.1).

$$F_i = \sum_{j \in S\{i\}} (s_{ij} + m_{ij} + w_{ij} + p_{ij}) \tag{2.1}$$

Where; i : Job type,

j : Station no,

s_{ij} : Setup time needed by job i at station j,

m_{ij} : Transportation time necessary for moving job i from station j to the next station on its route,

w_{ij} : Queue waiting time of job i at station j's queue,

p_{ij} : Processing time of job i at station j,

$S\{i\}$: The set of stations which are placed on job i's route.

2.2.2. Flow time prediction and/or due-date assignment models

In this study, two *PDDAMs* and two *CDDAMs* are used to estimate the flowtime of a job whenever it arrives to the shop. Transportation times between the workstations are assumed to be deterministic and previously known. Due to being deterministic and previously known, total transportation times for each job are included directly into the flow time calculations in accordance with their routes in all *DDAMs* considered in this study. Setup times are not taken into account in all *DDAMs* as they are assumed to be zero. Thus, in all *DDAMs*, estimation of terms p_j and w_j in Eq. (1) will be enough for flowtime estimation of each job. Estimation of these two flowtime components (p_j and w_j) is performed by using two *CDDAMs*, and two *PDDAMs*. Detailed information about the selected *CDDAMs* (*DTWK*, *DPPW*) and *PDDAMs* (*ADRES*, *LDP*) and their mathematical expressions are given next.

2.2.2.1. Due-date assignment model with DTWK

According to *TWK* rule, due dates of jobs are assigned according to their total amount of work. For convenience mathematical expression is given as follows:

$$d_i = r_i + kp_i \tag{2.2}$$

The due date allowance factor *k* would be chosen separately for each system configuration considered in order to achieve a given average flow allowance.

From Eq. (2.2), it is seen that the same degree of allowance is given to all jobs based only on their total amount of work. It is apparent that *TWK* rule does not take current shop information into account when assigning due date of a job. Due to this fact, it is impossible to estimate job flowtime dynamically by using, the regular *TWK* rule, which is accepted as a static and job character related due date method by Cheng et al. (1998).

To overcome this problem Cheng et al. constructed a modified form of *TWK* method by employing a dynamic due date allowance factor *k*. *DTWK*, which is a modified version of total work content (*TWK*) rule, can be constructed by employing a dynamic due date allowance factor *k*. Among the simple and easy to implement due date methods, *TWK* achieves the best performance for tardiness related performance criteria (Baker, 1984). The standard *TWK* is a static and job character-related due date assignment method; that is, it issues the same degree of tightness to all jobs based only on their job file information. If two jobs have the same amount of work, the same allowance will be given to them regardless of what the current shop load is, i.e. whether heavy or moderate. This kind of due date assignment lacks the means of estimating job flow time dynamically which takes explicitly account of current shop information. When the shop load is heavy, a relatively longer flow time allowance should be assigned to an arriving job; in the opposite case, a shorter allowance should be given (Cheng et al., 1998). Being a powerful conventional due date assignment rule, *DTWK* is selected in order to test the performance of the proposed statistical prediction models.

The details of mathematical definition of this technique can be found in Cheng et al. (1998)'s paper. If N_s denote the number of jobs in the system, λ denote the average job arrival rate and F denote the job flow time, then Little's law for a shop in steady state can be expressed by

$$E(N_S) = \lambda\, E(F) \tag{2.3}$$

Where; E (.) is the expected value operator. If it is assumed that the shop load is relatively steady for a short period of time, then any given time t, it can be approximated the average flow time of a job F_t, in the shop with N_s number of jobs in this period as:

$$F_t = N_{st} / \lambda \tag{2.4}$$

Thus, the dynamic allowance factor for a job newly arrived at time t would be determined by the current average flow time. Denoting the mean operation processing time and average number of operations per job by μ_q and μ_g, respectively, we see that $\mu_q\mu_g$ is the average total job processing time. Let k_t denote the real tightness level at the time t when a new job arrives, then

$$k_t = F_t / (\mu_p \mu_g) \tag{2.5}$$

To prevent applying allowance factors less than one, we use *max* [*1, k_t*] instead of k_t and define the corresponding dynamic due date by equation 6.

$$d_i = r_i + \max[1, k_t] \sum_{j=1}^{m_i} p_{ij} \tag{2.6}$$

Where; d_i is the due date assigned to job *i*, r_i is the arrival time of job *i*, p_{ij} is the processing time of the j^{th} operation of job *i* and m_i is total number of operations of job *i*. Substituting equations (2.4) and (2.5) into equation (2.6), we have the dynamic *TWK* (*DTWK*) formula;

$$d_i = r_i + \max\left[1, \frac{N_{st}}{\lambda \mu_p \mu_g}\right] \sum_{j=1}^{m_i} p_{ij} \tag{2.7}$$

In this formula, the parameters concerning the average job and shop characteristics are available, and the number of jobs in the system, N_{st}, is known at the time each job arrives, so that the dynamic due date can be determined.

In fact, the $\max\left[1, \frac{N_{st}}{\lambda \mu_p \mu_g}\right] \sum_{j=1}^{m_i} p_{ij}$ term of Cheng's *DTWK* formula represents the estimated flowtime of job *i*. Note that, differences between the term $\max\left[1, \frac{N_{st}}{\lambda \mu_p \mu_g}\right] \sum_{j=1}^{m_i} p_{ij}$ and Eq. (2.1) are transportation times and setup times of job *i*. As mentioned in section 2.2.2, in our job shop system, transportation times between the workstations are assumed to be deterministic and previously known (see Table 2.4). Also, setup times are not considered. In order to compare the performance of *DTWK* with other *DDAMs* (*DPPW, ADRES,* and *LDP*), transportation times are needed to be included in Eq. (2.7). Thus, Cheng's *DTWK* formula is adapted to our job shop system by only adding m_{ij} term. By this way, comparison of all DDAMs is achieved under the same system basis. The modified Cheng's DTWK formula is given in Eq. (2.8):

$$d_i = r_i + \max\left[1, \frac{N_{st}}{\lambda \mu_p \mu_g}\right] \sum_{j=1}^{m_i} p_{ij} + m_{ij} \tag{2.8}$$

2.2.2.2. Due date assignment model with DPPW

According to *PPW* rule, due dates of jobs are assigned according to the job processing time plus some multiple of the number of operation. For convenience, mathematical expression is given as follows:

$$d_i = r_i + \sum_{j=1}^{m_i} p_{ij} + km_i \tag{2.9}$$

The due date allowance factor k would be chosen separately for any system configuration considered in order to achieve a given average flow allowance. From Eq. (2.9), it is seen that some degree of allowance is given to all jobs based on their job processing time plus some multiple of the number of operation. It is apparent that *PPW* rule does not take current shop information into account when assigning due date of a job. Due to this fact, it is impossible to estimate job flowtime dynamically by using, the regular *PPW* rule, which is accepted as a static and job character related due date method. To overcome this problem, a modified version of *PPW* which dynamically updates the allowance factor k was proposed.

Formal definition of this technique can be found in Cheng et al. (1998). Denoting the total number of jobs in the queues of each machine by N_q, Little's law can be written as

$$E(N_q) = \lambda\, E(W) \tag{2.10}$$

Where W is the job waiting time. Then, at any given time t for a short period of steady state, the average waiting time for job with a mean number of operations μ_q can be approximated as

$$W_t = N_{qt} / \lambda \tag{2.11}$$

The corresponding estimated waiting time for a new job with m_i number of operations can be determined by multiplying m_i and dividing by μ_g $\left(W_i m_i / \mu_g\right)$.

Thus, the dynamic *PPW* due date (*DPPW*) is,

$$d_i = r_i + \sum_{j=1}^{m_i} p_{ij} + \frac{N_{qt}\, m_i}{\lambda\, \mu_g} \tag{2.12}$$

The $\sum_{j=1}^{m_i} p_{ij} + \frac{N_{qt}\, m_i}{\lambda\, \mu_g}$ term of Cheng's *DPPW* formula represents estimated flowtime of job *i*. Note that, differences between the term $\sum_{j=1}^{m_i} p_{ij} + \frac{N_{qt}\, m_i}{\lambda\, \mu_g}$ and Eq. (2.1) are transportation times and setup times of job *i*. By the same reason stated in section 2.2.2.2, transportation times are needed to be included in Eq. (2.12). Thus, Cheng's *DPPW* formula is adapted to our job shop system by only adding m_{ij} term. By this way, comparison of all DDAMs is achieved under the same system basis. The modified Cheng's DPPW formula is given in Eq. (2.13).

$$d_i = r_i + \sum_{j=1}^{m_i} p_{ij} + \frac{N_{qt}\, m_i}{\lambda\, \mu_g} + m_{ij} \tag{2.13}$$

2.2.2.3. Due date assignment model with ADRES

The first *PDDAM* is *ADRES*. *ADRES*, which is an interesting variant on simple smoothing, has an important advantage over normal smoothing models. This is mainly because of the manner in which the smoothing constant is chosen. In *ADRES* smoothing there is no requirement to actually choose an *α* value. The word adaptive in its name gives a clue to how the model works. The *α* value in the *ADRES* model is not just a single number, but rather adapts to the data (Wilson et al., 2002). The proposed due date assignment method, which is named as *ADRES,* defined in Eq. (2.14).

$$d_i = r_i + \sum_{j \in S\{i\}} m_{ij} + \sum_{j \in S\{i\}} w'_{ij} + \overline{p_i} \tag{2.14}$$

Where; $\sum_{j \in S\{i\}} w'_{ij}$ is sum of the most recent estimated queue waiting time for each station placed on job *i*'s route. m_{ij} is transportation time necessary for moving job *i* from station *j* to the next station on its route. For each type of job, its mean operation processing time is calculated from its processing time distribution for each station on its route. Then mean operation processing times are added up to find the mean total processing time of job i, which is represented by $\bar{p}_i$. At last, r_i, arrival time of job i to the system is added to assign due date of job i. Note that, whenever a job arrives to the job shop, Eq. (2.14) is used to assign due-dates.

In a dynamic job shop, where the jobs of various types enter and leave the production system continually in a random manner, the queuing time of a job (i.e. the time that the job spends at work centers without being worked on, mainly because there are other jobs ahead of it) normally accounts for the major portion (>90% in some case) of its lead time (Plossl, 1985; Chang, 1997). Besides being major portion of jobs lead time, its ambiguousness makes estimation of queue waiting time increasingly important especially in such complex systems. Estimation of job i's queue waiting time (w'_{ij}) for each station on its route is determined by using *ADRES* technique because of its simplicity and ability to adapt to changing circumstances. *ADRES* technique uses only two types of data for the purpose of estimating future values of the queue waiting times. One of them is actual queue waiting times of each station and the other is the last estimated queue waiting times of each station. Formal representation of this technique is given by Eq. (2.15).

$$w'_{(i+1)j} = \alpha_{ij} w_{ij} + (1 - \alpha_{ij}) w'_{ij} \tag{2.15}$$

Where; $w'_{(i+1)j}$: ADRES value of actual waiting time for job $i+1$ at station j,

w_{ij} : The most recent actual queue waiting time of job i at station j,

w'_{ij} : The most recent estimated queue waiting time of job i at station j.

$$\alpha_{ij} = \left| S_{ij} / A_{ij} \right| \tag{2.16}$$

Where; α_{ij} : Smoothing value for order i at station j queue

S_{ij} : Smoothed error of order i at station j queue

A_{ij} : Absolute smoothed error of order i at station j queue

$$S_{ij} = \beta e_{ij} + (1-\beta)S_{(i-1)j} \quad \text{(Smoothed Error)} \qquad (2.17)$$

Where;

β : Smoothing constant

$$A_{ij} = \beta\left|e_{ij}\right| + (1-\beta)A_{(i-1)j} \quad \text{(Absolute Smoothed Error)} \qquad (2.18)$$

$$e_{ij} = w_{ij} - w'_{ij} \quad \text{(Error)} \qquad (2.19)$$

In most cases, β is assigned a value of either 0.1 or 0.2. In this study, 0.1 is chosen for β after preliminary runs.

2.2.2.4. Due date assignment model with LDP

The second *PDDAM* is *LDP* model. LDP is just a special case of ADRES when we set the parameter α constantly equal to 1. In this model due date of a job is also calculated by using Eq. (2.14). This model resembles the *ADRES* model except the technique uses the most recent actual queue waiting time of orders for estimating the queue waiting time of next order.

In LDP, actual queue waiting time of job *i* at station *j* is used as the estimation of queue waiting time for job *i+1* at station *j*. There is no smoothing constant in this technique. Mathematical expression of this model is easier as given in Eq. (2.20).

$$w'_{(i+1)j} = w_{ij} \qquad (2.20)$$

Where; $w'_{(i+1)j}$ is estimated queue waiting time of job *i+1* at station *j,*
w_{ij} is the most recent actual queue waiting time of job *i*.

2.2.3. Dispatching rules

A priority dispatching rule determines which job (operation) to begin next when machine becomes free (Baker, 1984). Generally, the objective of scheduling rules is two fold: first, to meet due date, and second, to minimize flowtime (Vig et al., 1991). A number of dispatching rules have been proposed in the literature over the past years, but there has been no rule which dominates in both objectives (under all shop conditions).

As it was stated by Vig et al. (1991), priority rules which are referred to dispatching rules are placed into one of three main categories: random, static and dynamic. Random priority rules are arbitrary, disregarding both job and shop information. *FIFO* dispatching rule can be included in this category. Static priority rules are based on the invariant job or shop information. Two examples are *SPT* and *EDD*. Dynamic rules are the most complex ones, requiring more information than static and random priority rules. They require continuous updating of job priorities. *S/RO* can be included in this category.

In addition to this classification, priority rules can be classified either operation based or job based. Operation based priority (dispatching) rules use information about pending operations of available jobs, whereas job based dispatching rules use only summary information about the jobs (Gee et al., 1993).

The choice of dispatching rule was another important consideration in this research. For this purpose, four different dispatching rules were selected among the three different categories of dispatching rules to measure the performance of them with respect to the selected performance measures. Another objective of this selection was to test the robustness of due date assignment models under different dispatching rules. Selected rules with their categories and characteristics are as follows.

- First come first served (*FCFS*): A random priority rule which loads the jobs in the order which arrive to the queue. No calculation is needed for this rule and it is one of the most used dispatching rules in practice.
- Earliest due date (*EDD*): A static priority rule. Characteristic of this rule is to prioritize queued jobs according to their due date immanency. It is easy and one of the most used rule in practice.
- Shortest processing time (*SPT*): A static priority rule. Characteristic of this rule is to assign job urgency to the job in queue which requires the least estimated processing time.
- Slack per remaining operation (*S/RO*): A dynamic priority rule. Characteristic of this rule is to give priority to an order which's ratio of remaining slack to remaining number of operation is minimum. It needs more information than

the other rules and necessity of updating the priorities constantly makes the use of this rule more difficult.

2.2.4. Shop utilization

Utilization rates are generally selected as 85% and 90% to represent moderate and heavy shop load level respectively in many studies (Ragartz et al., 1984a, Melnyk et al., 1991, Philipoom et al., 1994, 2000). In general, due date based dispatching rules are expected to work well at low utilization levels. In this study in order to test this phenomenon and the robustness of the due date assignment methods four shop load levels are determined. They are: balanced shop with load level 70%, 80%, 90%, respectively and unbalanced shop. Furthermore, these shop load levels are named as Case 1 (Balanced and 70% shop load level), Case 2 (Balanced and 80% load level for each station), Case 3 (Balanced and 90% load level for each station), and Case 4 (Unbalanced and station load levels differ from each other).

2.2.5. Performance measurements

Basically three performance measures are considered in this study. They are *MAPE, MPE, and MT*. *MAPE* measures accuracy of the due date assignment methods, whereas *MPE* measures bias of them. Furthermore, average total flow time ($\overline{F}$), mean earliness (*ME*), percentage of tardy job (*T%*) and percentage of early job (*E%*) are collected to provide additional insights in the performance of the due date assignment methods.

2.3. Experimental study

A three-phase investigation is required for the evaluation of proposed due date assignment models and the investigation of the relationships of job shop factors. First, simulation models of a job shop are developed, coded, validated and verified. Second appropriate β parameter is determined for the *ADRES* model. Finally, a factorial design is used to investigate the effects of job shop factors on the due date performance.

2.3.1. The job shop simulation model

The developed simulation model represents a hypothetical multi stage job shop production system containing ten stations. Each station contains parallel identical machines. The number of machine in each station changes case by case and given in Table 2.1. The arrival of jobs to the job shop is assumed to be random with interarrival times that are exponentially distributed with mean of 1.5 time units. Six different types of jobs can arrive to the system. They are called *type 1 job*, *type 2 job*, *type 3 job, type 4 job, type 5 job and type 6 job,* respectively. The arrival probabilities of jobs to the system are set to 0.15, 0.15, 0.2, 0.15, 0.15 and 0.2, respectively. *Type 1 job* has 4 operations, *type 2 job* has 5 operations, *type 3 job* has 5 operations, *type 4 job* has 4 operations, *type 5 job* has 3 operations and *type 6 job* has 5 operations. The routes of each job type are assumed to be known and given in Table 2.2. The processing time of each job are assumed to be uniformly distributed and changes according to the type and/or route of the job. Processing times according to job type and stations visited on its route are given in Table 2.3. Transportation times between stations are assumed to be known previously and given in Table 2.4.

Table 2.1. Number of machines in each station

	Work Station No									
	1	2	3	4	5	6	7	8	9	10
Case1	10	9	9	12	9	7	8	9	10	11
Case2	9	8	8	11	8	6	7	8	9	9
Case3	8	7	7	9	7	6	6	7	8	8
Case4	9	7	14	13	10	6	6	7	12	8

Table 2.2. Routes of job type

Job Type	Routes of the job (Station no)
1	1,3,4,5
2	5,6,3,8,9
3	1,3,2,7,5
4	1,8,4,10
5	6,9,10
6	2,7,4,8,10

Table 2.3. Process time of jobs according to routes

Job Type	Process Times of Jobs According to Stations
1	(15,21), (12, 18), (21, 30), (12, 40)
2	(18, 26), (20,32), (26,30),(18,20),(30,41)
3	(21, 25), (10, 20), (20, 25), (15, 25), (15, 25)
4	(21, 25), (16, 20), (22, 30), (20, 25)
5	(20, 25), (30, 40), (20, 25)
6	(22, 27), (16, 25), (20, 30), (16, 20),(20,25)

Other simulation model characteristics are:

- Each machine has constant availability, i.e. machine breakdowns and maintenance are not considered.
- The model does not include assembly operations.
- Each operation must be performed at the predetermined station. There is not any alternative routings.
- Preemption of an operation is not allowed.
- Only single operation can be processed at a time for a particular job type.
- Transportation time between stations is deterministic and solely depends on the distance between stations.
- Due to orders are released to the shop as soon as they arrive no order review release policies are included.

Table 2.4. Transportation time of orders between stations (St) (in time units)

	St 1	St2	St3	St 4	St 5	St6	St7	St8	St9	St10
St 1	0	3	6	9	12	15	18	21	24	27
St 2	3	0	3	6	9	12	15	18	21	24
St3	6	3	0	3	6	9	12	15	18	21
St4	9	6	3	0	3	6	9	12	15	18
St 5	12	9	6	3	0	3	6	9	12	15
St6	15	12	9	6	3	0	3	6	9	12
St7	18	15	12	9	6	3	0	3	6	9
St8	21	18	15	12	9	6	3	0	3	6
St9	24	21	18	15	12	9	6	3	0	3
St10	27	24	21	18	15	12	9	6	3	0

2.3.2. Experimental procedure

Full factorial design is employed to evaluate *DDAMs* and to investigate the relationships between different shop factors. The design includes two *CDDAMs* and two *PDDAMs*, four dispatching rules, and four shop load levels. Thus 64 experiments are necessary (i.e. 4x4x4) to investigate all factor level combinations. Data is collected on seven performance measures to evaluate the performance of the due date assignment models. These are *MAPE*, *MPE*, $\bar{F}$, *MT*, *ME*, *T%* and *E%*. Among them *MAPE*, *MPE*, *MT* simulation results and *ANOVA* results are reported in a tabular format. Values in the Tables are average of 25 replications. The simulation model of the system runs for 14400 time units. Warm-up period for the system is determined as 1440 time units after preliminary runs. The experiments are performed using 25 replications of each treatment, thus minimizing variability in the results. Common random numbers are applied when we are comparing two or more alternative system configuration instead of investigating a single configuration (Law et al., 2000).

2.4. Results

2.4.1. Analysis of variance

A three factor *ANOVA* method with fixed factor is applied to test the effects of the shop load level, dispatching rule and due date assignment model on the performance measurements. The *ANOVA* results reported in Table 2.5, Table 2.6, and Table 2.7 show that *MAPE*, *MPE* and *MT* performance measures are significantly affected by the variations in due date model, dispatching rules and shop load level. All *p-values* are significantly less than 0.05. Therefore, the due date assignment model, dispatching rule and shop load level and their interactions have significant effect on due date performance. The main reason for this situation is appropriated to the negative effects of congestion on the system as was mentioned by Vig et al. (1991). According to their study, as shop congestion increases, the system becomes less stable, causing increases in flow time variability which deteriorates the predictability of the shop. Our results confirm these findings.

Table 2.5. Analyses of variance for *MAPE*

Source	*Type III Sum of Squares*	*DF*	*MS*	*F*	*Sig.*
Corrected Model	46789.76[a]	63	742.6946	252.483	.000
Intercept	200964.4	1	200964.4	68318.91	.000
Shoplev (A)	24619.69	3	8206.562	2789.864	.000
Dispatch (B)	3032.032	3	1010.677	343.5851	.000
DDAM (C)	5167.169	3	1722.39	585.5355	.000
AB	2972.925	9	330.325	112.2957	.000
AC	1865.294	9	207.2549	70.45741	.000
BC	4592.939	9	510.3265	173.4882	.000
ABC	4539.714	27	168.1376	57.15926	.000
Error	4518.241	1536	2.941563		.000
Total	252272.4	1600			.000
Corrected Total	51308	1599			.000

[a] R squared=.912 (Adjusted R Squared = .908)

Table 2.6. Analyses of variance for *MPE*

Source	*Type III Sum of Squares*	*DF*	*MS*	*F*	*Sig.*
Corrected Model	66700.33[a]	63	1058.735	454.4917	.000
Intercept	31350.01	1	31350.01	13457.86	.000
Shoplev (A)	99.93628	3	33.31209	14.30014	.000
Dispatch (B)	4077.767	3	1359.256	583.4983	.000
DDAM (C)	36294.62	3	12098.21	5193.492	.000
AB	3703	9	411.4444	176.624	.000
AC	19084.8	9	2120.534	910.2982	.000
BC	1826.253	9	202.917	87.1078	.000
ABC	1613.954	27	59.77608	25.66055	.000
Error	3578.102	1536	2.329494		.000
Total	101628.4	1600			.000
Corrected Total	70278.44	1599			.000

[a] R squared=.949(Adjusted R Squared = .947)

Table 2.7. Analyses of variance for *MT*

Source	*Type III Sum of Squares*	*DF*	*MS*	*F*	*Sig.*
Corrected Model	253873.8[a]	63	4029.742494	125.41	.000
Intercept	694692.7	1	694692.7143	21619.61	.000
Shoplev (A)	146234.8	3	48744.93362	1516.996	.000
Dispatch (B)	21245.76	3	7081.920117	220.3972	.000
DDAM (C)	19270.71	3	6423.568928	199.9086	.000
AB	26364.72	9	2929.413794	91.1666	.000
AC	8608.215	9	956.4682782	29.76635	.000
BC	13570.6	9	1507.84389	46.92577	.000
ABC	18578.98	27	688.1102016	21.41475	.000
Error	49355.57	1536	32.13253264		.000
Total	997922.1	1600			.000

Corrected Total	303229.3	1599	.000

[a] R squared=.837 (Adjusted R Squared = .831)

2.4.2. Comparisons of differences

MAPE values with respect to due date assignment models are shown for case 1 in Figure 2.1. These values show the superiority of the prediction models to each other and also how the size of the prediction errors changes while using different dispatching rules. In this case, prediction errors are very low for each due date assignment method and none of the prediction model dominates others for each dispatching rule. Also, there is no significant difference between the *MAPE* results of due date assignment models. *MAPE* values are summarized in Table 2.8 for all cases together with due date assignment models and dispatching rules. From Table 2.8 it is seen that minimum *MAPE* value is obtained by *ADRES* model using together with *FIFO* dispatching rule.

In Figure 2.2., *MAPE* values with respect to due date assignment models are shown for case 2. In this case, all *MAPE* values increased except obtained by *ADRES* model together with *FIFO* dispatching rule. Note that, *MAPE* value which is obtained by *ADRES* model together with *FIFO* dispatching rule remained unchanged. From Table 2.8 it is seen that minimum *MAPE* value is obtained again by *ADRES* model using *FIFO* rule.

In Figure 2.3, *MAPE* values with respect to due date assignment models are shown for case 3. In this case, it is apparently seen that *MAPE* values deteriorates rapidly for all due dates together with all dispatching rules. However, *MAPE* performances of *PDDAMs* dominate *CDDAMs* in the case of utilizing both *PDDAMs* with *EDD* and *FIFO* dispatching rule. Also, *DTWK* model's prediction accuracy is much more deteriorated than other *DDAMs* for all dispatching rules considered. Thus, it could be concluded that *DTWK* model's *MAPE* performance is disproportional to job shop load level. Also, this conclusion is acceptable for other models when *SPT dispatching* rule is utilized (except *ADRES* model), and for *LDP* rule when *S\RO* dispatching rule is utilized. As in the first two cases minimum *MAPE* value is obtained by *ADRES* model using the *FIFO* rule.

In Figure 2.4, *MAPE* values with respect to due date assignment models for each dispatching rule utilized are shown for case 4. In the case of the unbalanced shop load, *MAPE* values of each due date assignment model are varies for each dispatching rule considered. *MAPE* performance of *ADRES*, *LDP*, and *DPPW* are reasonable and also close to each other whenever utilized together with *EDD* and *FIFO* dispatching rules. However, other dispatching rules exhibit worse performance whenever utilized with these *DDAMs*. Note that, *CDDAMs* exhibit better *MAPE* performance than *PDDAMs* in the case of utilized with *SPT* dispatching rule. But, this is not true for S/RO dispatching rule.

Table 2.8. *MAPE* values for all cases together with *DDAM*s and dispatching rules

Shop load level	*Due date assignment model*	*Dispatching rule*			
		EDD	*FIFO*	*SPT*	*S/RO*
Balanced 70%	*ADRES*	5.92	5.85*	6.05	5.99
	DPPW	6.22	6.08*	6.38	6.48
	DTWK	6.75*	6.87	6.89	6.78
	LDP	7.97	8.03	7.91	7.88*
Balanced 80%	*ADRES*	7.38	5.85*	8.88	7.87
	DPPW	7.91	7.57*	9.41	9.50
	DTWK	7.76*	7.87	8.24	7.96
	LDP	11.15	11.03	10.40*	11.22
Balanced 90%	*ADRES*	9.96	9.17*	26.46	12.10
	DPPW	10.67	9.59*	24.95	26.25
	DTWK	11.49*	12.15	18.30	13.83
	LDP	24.44	22.91	18.28*	24.37
Unbalanced	*ADRES*	8.47	8.28*	16.06	10.04
	DPPW	9.06	8.57*	15.79	16.94
	DTWK	9.22*	9.25	11.13	10.16
	LDP	15.96	15.34	12.38*	15.43

(*) minimum MAPE values

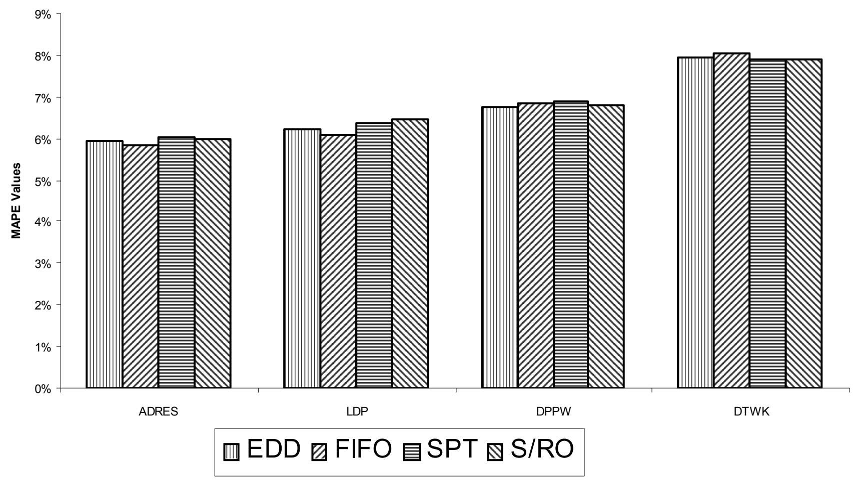


Figure 2.1. MAPE values for case 1

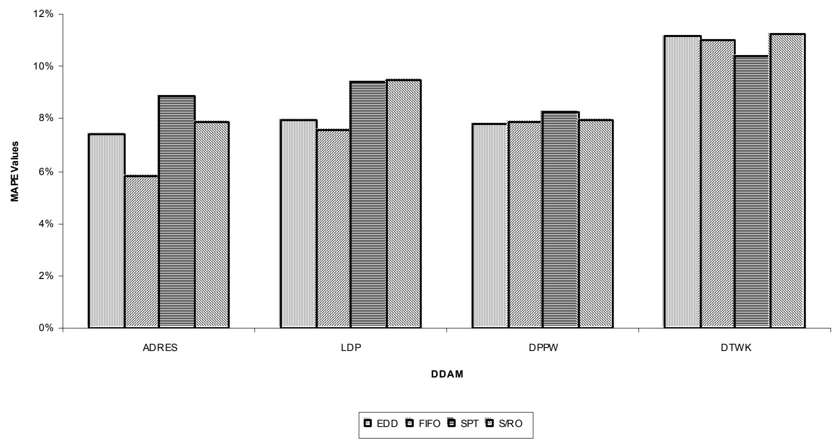


Figure 2.2. *MAPE* values for case 2

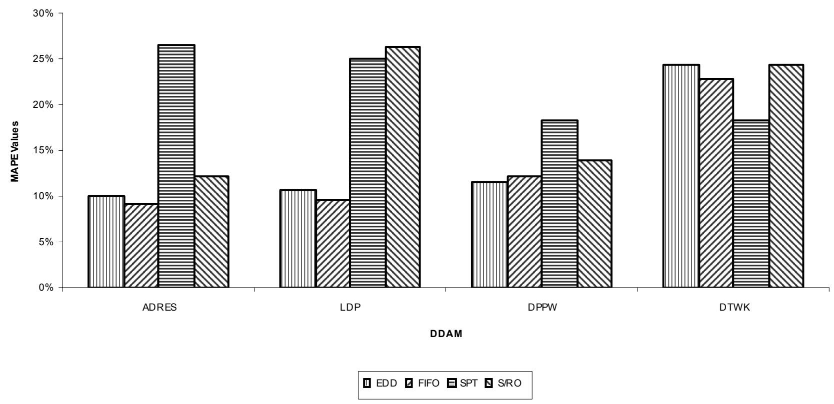


Figure 2.3. *MAPE* values for case 3

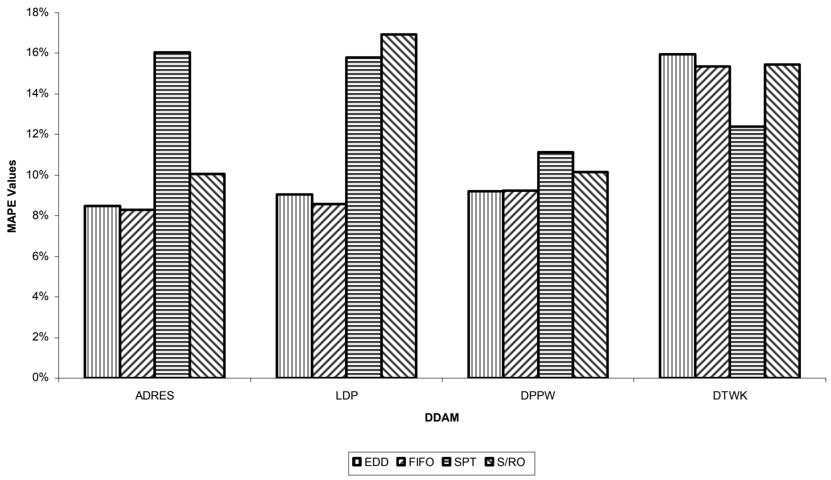


Figure 2.4. MAPE values for case 4

MPE performance measurement represents the bias of the due date assignment models. For the first two cases, proposed and conventional *DDAMs* are positive biased. However, it is apparently seen that *MPE* values obtained together with *DTWK* model are notably higher than the others. Nevertheless, for the last two cases, negative biases are observed for all *DDAMs* except *DTWK* model. Negative bias is observed in the case of utilizing *SPT* and *S/RO* dispatching rules together with all *DDAMs* except *DTWK* model. This is mainly due to the fact that *SPT* and *S/RO* dispatching rules aims to minimize flowtime of jobs actually which causes negative bias. *MPE* values related with all *DDAMs* together with all dispatching rules are summarized case by case in Table 2.9.

Table 2.9. *MPE* values for all cases with *DDAM*s and dispatching rules

Shop load level	*Due date assignment model*	*Dispatching rule*			
		EDD	*FIFO*	*SPT*	*S/RO*
Balanced 70%	*ADRES*	3.56	3.89	3.25	3.47
	DPPW	4.35	4.53	4.13	4.19
	DTWK	3.49	3.56	3.46	3.40
	LDP	5.91	5.98	5.72	5.98
Balanced 80%	*ADRES*	3.26	3.89	1.63	2.88
	DPPW	4.53	5.16	3.14	3.69
	DTWK	2.54	2.89	2.27	2.29
	LDP	9.62	9.48	8.77	9.84
Balanced 90%	*ADRES*	1.99	4.24	-12.69	0.64
	DPPW	4.12	5.52	-5.82	-6.89
	DTWK	-1.28	-0.25	-7.07	-2.54
	LDP	23.64	22.01	16.94	23.64
Unbalanced	*ADRES*	3.47	4.28	-3.29	2.51
	DPPW	4.60	5.16	-0.16	-1.65
	DTWK	1.25	1.30	-1.14	0.33
	LDP	14.89	14.20	10.93	14.47

The philosophy of *JIT* emphasizes both tardiness and earliness is undesirable. The economic implications of tardiness are often related to losses resulting from failure to meet the due date, such as penalties and losing customer's goodwill. Some studies also considered the earliness effect, but separately (Cheng et al., 1997). Philipoom (2000) defined tardiness penalty as the penalty for poor delivery reliability which is the ability to consistently meet promised delivery date. Melnyk *et al.* (1989) and Hendry (1994) defined mean tardiness and proportion of tardy jobs as a measure of delivery performance.

From Table 2.10, it is seen that none of the *DDAM* dominates others for each dispatching rule for case 1. Case 2 and case 3 results reveal that *LDP* model has the worst *MT* performance. Also, *MT* performance for all *DDAMs* deteriorates as shop load level increases. For the three cases, minimum *MT* value is obtained by the *ADRES* model utilized with *FIFO* dispatching rule. Results obtained for case 4 are consistent with the first three cases. The best result is obtained by *ADRES* model utilized together with *EDD* dispatching rule.

Table 2.10. *MT* values for all cases with *DDAM*s and dispatching rules

Shop load level	*Due date assignment model*	*Dispatching rule*			
		EDD	*FIFO*	*SPT*	*S/RO*
Balanced 70%	*ADRES*	9.79	9.71	9.99	10.09
	DPPW	10.21	10.05	10.44	10.56
	DTWK	10.45	10.63	10.90	11.88
	LDP	12.38	12.49	12.45	12.66
Balanced 80%	*ADRES*	12.52	9.71	14.72	13.76
	DPPW	13.16	13.07	16.01	15.58
	DTWK	12.53	12.58	14.74	14.46
	LDP	18.38	17.99	18.11	19.71
Balanced 90%	*ADRES*	19.98	19.29	52.40	25.16
	DPPW	20.21	20.26	45.74	49.40
	DTWK	20.56	21.63	64.75	26.29
	LDP	48.88	45.30	45.56	51.70
Unbalanced	*ADRES*	14.48	14.50	26.22	17.54
	DPPW	15.02	15.09	25.25	26.97
	DTWK	14.91	15.29	26.91	19.04
	LDP	28.60	27.15	25.89	29.91

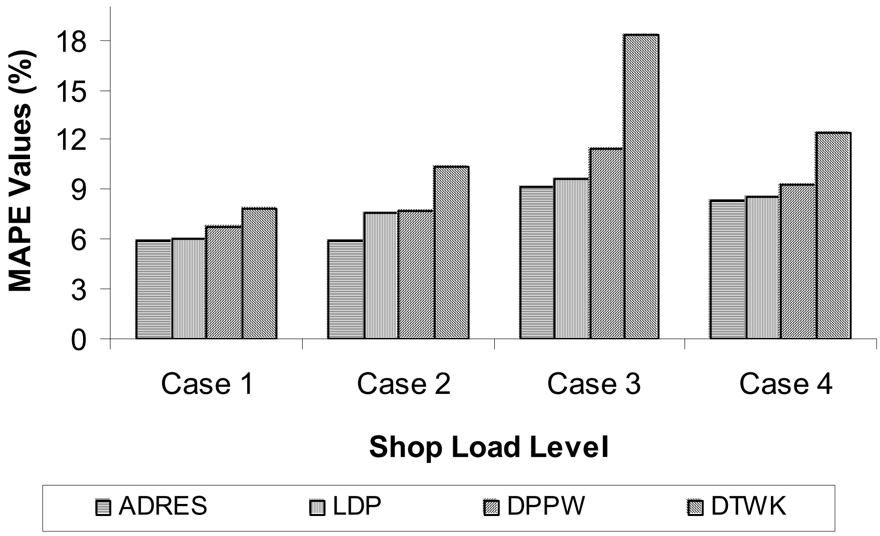


Figure 2.5. The best MAPE values for all DDAMs

2.5. Conclusions

In this study, a new approach for due date assignment in a job shop is presented. It is shown that *ADRES* model together with *FIFO* and *EDD* dispatching rule dominates other *DDAMs* considered. Thus, it could be said that more reliable due dates could be assigned through proposed *ADRES* model together with *FIFO* and *EDD* dispatching rules. The main results obtained from this research are as follows:

From Figure 5, it is apparently seen that both *PDDAMs* exhibit better performance than the *CDDAMs* in terms of *MAPE* performance measurement. Thus, it should be noted that accurate and precise due dates can be assigned by using both *PDDAMs*.

Among the *CDDAMs DTWK*, together with all dispatching rule, exhibits the worst *MAPE* performance for all cases. The problem with *DTWK* model is that dynamic allowance factor for a job newly arrived at time *t* determined by the current average flow time. Thus, *DTWK* model does not consider neither overall nor on jobs route queue waiting times of jobs. This causes estimation of flow times to be insensitive to the queue waiting times on job's route and also difficulties while estimating flow time for a job accurately.

As shop load level congested, *MAPE* performance of all *DDAMs* except *DTWK* model generally deteriorates while utilizing together with *SPT* dispatching rule. This can be attributed to the characteristic of *SPT* rule towards minimizing total flow time while not considering the queue waiting times or due dates. Philipoom (2000) gave a good example in order to explain the problem with *SPT*. He told that, a job with a large processing time may slip through the shop quickly if it arrives at the machine when it is idle. However, the job can easily delayed by a stream of arriving jobs with shorter processing times.

MPE performance measurement represents the bias of the prediction model. *MPE* values of each model are close to each other for case 1, except *DTWK* model with all dispatching rules. For the first two cases, models estimate flowtime smaller than the actual flow times which causes the *MPE* values to become positive. Congestion of shop load level causes the *MPE* values to become negative for some dispatching rules.

Consistent with the literature, results shown that the performance of models is highly dependent on the dispatching rules used to sequence the jobs and shop load level. *FIFO* is a random, the most basic and simple dispatching rule compared to all of its counterparts. It uses neither job related nor shop related information. On the contrary, *S/RO* is a dynamic, more sophisticated dispatching rule. In spite of its simplicity the results indicates that there is no significant difference between the results of *FIFO* and *S/RO* (Baykasoglu, *et al*. 2005).

Performance of the models deteriorates as the average utilization of the stations increases. Nevertheless, for each load level model's due date performances are close to each other except *DTWK* model. However, if all load levels are considered, most of the best results are obtained by using the *ADRES* model with *FIFO* dispatching rule according to the *MAPE* performance criterion. This can be attributed to the usage of information about the congestion along a job's routing (like *ADRES*, *LDP*) which is more useful than knowing the general condition of the shop. As a result, the simpler due date assignment models, *ADRES* and *LDP* performed better than the more complex *DPPW* and *DTWK* models.

As discussed above *DTWK* model has the worst due date performance. However, among other models *DPPW* model's performance is worse than proposed due date assignment models. The main reason for this situation is that *DPPW* model uses shop based information while dynamically updating the flow time components (e.g., mean overall queue waiting time). This logic of *DPPW* model makes estimated job flow times insensitive to queue waiting times of each job on its route. Insensitiveness to the queue waiting times on jobs route causes inaccurate flow time estimation also due date assignment. However, proposed models dynamically update the queue waiting times of each job on its route by using the job based information.

When *MT* values are considered, excluding some exceptions, it can be easily seen that *MT* value of each model increases as the shop load level increases. It can also be seen that as the shop load level increases irregularities between *MT* values are also increase.

Consequently, we can conclude that the proposed models in this thesis can assign more accurate and precise due dates. Among the proposed models, *ADRES* model has the best performance whereas among the classical models *DPPW* model has the best performance. However, there is no single model based on a dispatching rule, dominates the others for all load levels for all performance criteria considered.

The future work for extending the present study should include investigations on alternative estimation techniques for the flowtime. Soft computing techniques namely genetic programming and neural networks can be considered as promising candidates.

CHAPTER 3

ORR FRAMEWORK AND A COMPARATIVE STUDY

3.1. Introduction

Shop floor is a dynamic environment and is an integral part of any manufacturing system. Due to its dynamic nature unexpected events continuously occur, and impose changes to previously planned activities. Thus, controlling activities in a shop floor in order to achieve the greatest efficiency and predictability of the manufacturing processes has an important role in a manufacturing system. In a shop floor, activities are controlled by using SFC methods. Melnyk and Ragatz (1988), stated that SFC consists of all activities directly responsible for managing the transformation of planned orders into a set of outputs. Five major functions of a complete SFC system are given as: (1) *Order Review/Release* (i.e., the process of managing the transition of the order from the planning system to the shop floor) (2) *Detailed Scheduling* (i.e., The process of matching demand with shop resources) (3) *Data Collection Monitoring* (i.e., The process of collecting information about such areas as job progress, resource usage, resource wear and comparing the collected data against a predetermined standard to identify "out-of-control" situations) (4) *Control/Feedback* (i.e., The activities needed to keep the other systems in the firm aware of the status of the shop floor and to correct "out-of-control" situations (5) *Order Disposition* (i.e., Those activities needed to close out the order on its completion). According to Melnyk et al. (1988) a major objective of SFC is to complete released orders in a timely and cost effective manner. Hopp et al. (1996) pointed out that a SFC satisfies the following four objectives:

1) It creates ideal production system,
2) It provides an enabling environment for the workers that make the entire production system easy to understand,

3) It integrates easily with other planning functions,
4) It has the flexibility to accommodate new ideas and changes.

The importance of SFC becomes much more critical especially in a dynamic and highly volatile environment such as job shop. A job shop is a flexible production facility that consists of a set of versatile machine centers or work centers and is capable of producing a wide variety of jobs. This type of flexibility results in more set-up time, more in-process inventory, complex scheduling, varying quality, poor delivery performance of jobs, etc. (Graves, 1986). Essentially, effective SFC overcomes all these types of problems.

Melnyk and Ragatz (1988) signified that the key to effective SFC lay not in controlling orders after release, but in controlling release. Thus, in order to get improved shop floor performance one must first stabilize the system condition with ORR function of SFC (i.e., controlling the rate at which jobs entered the shop) and then set the most appropriate dispatching rule for resulting system status. By this way, the management of the shop floor is supported by the other activities of the shop floor such as ORR which is ignored previously.

Stabilizing system status is important for predictiveness of the long-run performance of the system. The importance of this issue can be easily explained through queuing theory. It is well known from the queuing theory that in order to obtain accurate long-run performance measures of queuing systems such systems should be stable. For example, consider a $G/G/C/\infty/\infty$ queuing model. Assume that all servers are busy that means the current service rate of the system is $c\mu$. As mentioned above, accurate long-run performance measures can only be attained with stable systems. Thus, stability of the system must be provided. For our example, stability of the system can be provided by adjusting the average arrival rate λ smaller than the maximum service rate $c\mu$ (i.e., $\lambda<c\mu$). Otherwise, arrivals are occurring, on the average, faster than the system can handle them, all the servers will be continuously busy, and the waiting line will grow in length at an average rate of $(\lambda-c\mu)$ customers per time unit. Such a system is unstable,

and the long-run performance measures (L, L_Q, w, and w_Q) are again meaningless for such system. Thus, if the arrival rate does not controlled, shop floor's performance deteriorates even though utilizing the most sophisticated dispatching rule in the shop floor.

This issue is noticed by a number of researchers in the job shop scheduling literature. For example, in his seminal work, Little (1961) showed the relationship among WIP, throughput, and MLT theoretically. His work dictates that satisfactory throughput rates can be achieved with reasonable lead times by allowing WIP levels to a certain point. This argument is supported by a considerable number of works (Shimoyashiro et al., 1984, Browne and Davies, 1984).

3.2. What is ORR?

In its most basic definition ORR controls the flow of orders from the customer enquiry (i.e., planning system) to the shop floor (i.e., production control). ORR manages this flow by operation of four activities over four major components.

3.2.1 The activities of ORR

As mentioned before ORR manages the transition of orders from planning system to the shop floor. This transition process is carried out by the operation of some activities belong to ORR. ORR activities are particularly discussed by a number of researchers in the literature (i.e., Melnyk and Carter, (1987), Melnyk and Ragatz (1988), Bergamaschi et al., (1997)). Among them the first one is developed by Melnyk and Carter (1987). According to Melnyk and Carter (1987) and Melnyk and Ragatz (1988), ORR consists of three major activities; a. Order preparation, b. Review and evaluation, and c. Load leveling. In these studies, all orders received by the shop was accepted which was a common assumption of the published literature on ORR. Philipoom and Fry (1992) was the first study which relaxed this assumption by enabling rejection of some orders. According to the authors, in times of high shop congestion, it may be better to reject an order to allow the customer to seek another supplier than to accept the order and deliver it to the customer late. This improvement was recognized by Bergamashchi et al. (1997). According to these authors, a complete ORR system has three major parts; a. Order entry phase, b. PSP management phase, and c. Order release phase. According to the guideline laid by Bergamaschi et al. (1997) the activities of ORR was summarized as follows:

a. Order Entry Phase: The ‘order entry’ (OE) phase is defined to be the upstream interface of ORR with the planning system or directly with customers. This phase deals with first, the acceptance/rejection decision of orders to the planning system. Then deals with the order preparation. Order preparation ensures that all accepted orders has all of the information required by the shop floor personnel (i.e., determination of order’s routing, confirmation of the availability of required tooling, fixtures, materials, assignment of due dates etc.). After order acceptance, routing determination, confirmation of requirements, and due date assignment process, an order can place in the PSP which is the most significant component of the ORR.

b. PSP Management Phase: Orders that processed by OE phase are stored in the PSP storage area. It can be physical or electronic environment (i.e., database). If there is a physical environment for PSP then this environment should consist of physical raw materials for orders that passed OE phase. Otherwise, PSP consists of just the associated paperwork for the orders that passed OE phase. Orders are queued at this gateway according to their priority which is previously determined according to the satisfaction of some system performance measures.

c. The order release phase: The effectiveness of ORR directly depends on the operation of this phase. Once stored in the PSP orders must released to the shop floor according to a set of criteria. This release procedure is maintained by order release (OR) mechanisms. OR mechanism manages the flow of orders from PSP to the shop floor. This flow is controlled at two decision points. First OR mechanism determines whether the release of an order in PSP can take place. If an order release decided to take place second decision which is about the time of the release has to be made.

3.2.2 The components of ORR

ORR function operates with the cooperation of four major components. Up to date, the most recognized, detailed and comprehensible form of these components was given in Melnyk and Ragatz (1988). In the following, the components of ORR will be described briefly according to the guideline laid by Melnyk and Ragatz (1988).

a) The PSP
b) The shop floor
c) The planning system
d) The information system

a) The PSP: In literature, major part of the effectiveness of the ORR function attributed to management of the PSP. In this respect, PSP management is the major focus of attention. Thus, most of the previous studies are related to development and maintenance of PSP. As mentioned in subsection of the activities of ORR, orders that processed by OE phase are stored in the PSP storage area. These orders are considered as matured orders. PSP which consists of matured orders is known to be an interface between the planning system and the shop floor. Moreover, management of PSP provides the basis for the OR mechanism by which ORR function controls the flow of orders to the shop floor (Melnyk and Ragatz, 1988). The authors stated that PSP management can be described by specification of three elements: 1. Timing convention, 2. Triggering mechanism, and 3. Selection rule.

1. Timing convention: In its most basic definition, timing convention determines when a release can take place. This is done by monitoring conditions in the PSP and on the shop floor periodically or continuously. Thereby, two types of timing conventions are defined as either continuous or bucketed. In the case of continuous timing convention, an order can be released at any time during the system's operation. On the other hand, under the bucketing timing convention, an order can be released at periodic intervals during the system's operation. The type of the timing convention strictly related to sophistication level of PSP management.

2. The triggering mechanism: According to the timing convention only release times are determined. The triggering mechanism determines further when an order's release actually should take place. Three types of triggering mechanisms are used to determine the time of an order's release to the shop floor: a. Pool based triggering mechanisms, b. Shop based triggering mechanisms, and c. Both pool and shop based triggering mechanisms. Pool based triggering mechanisms determines the release time of an order according to the information about orders in the pool (i.e., release work when the pre-assigned release date for a job arrives). With shop based trigger mechanisms, decision about when to release an order is based on current conditions on the shop floor. Current conditions on the shop floor can be measured by either current workload or number of jobs. Sophistication level of the shop based triggering mechanisms strictly depends on the level of detail of the information they use on shop conditions (i.e., a shop based trigger which releases orders by looking at shop load by work center is more sophisticate than the one which releases orders by looking at aggregate shop load). Besides, they may consider only instantaneous conditions or may attempt to time-phase the shop conditions. According both pool and shop based triggering mechanisms, the decision about when to release a job is based strictly on information about both orders in the PSP and the shop condition.

3. Selection rules: Once a release has been triggered selection rules determines which jobs to release. Note that, in this sense not necessarily all but some of the pool based triggering mechanisms work as well as a selection rule. In fact, the PSP itself can be considered as a big queue in front of the whole production system. Thus, selection rules operate as a dispatching rule. Similar to dispatching rules, selection rules can be considered as either local or global. Whenever an order release takes place, local selection rules uses only order based information. On the other hand, global selection rules not only use only order based information but also use shop based information.

b) The shop floor: In the order release phase, ORR functions via an OR mechanism. One of the aim of an OR mechanism is to provide a stable shop condition (i.e., eliminates peak and valleys of the shop load). To achieve this objective such mechanisms try to release orders to the shop floor in such a way that load by work center and/or total shop load remain relatively constant (i.e., shop is not overloaded or underloaded). To control either the whole shop load or load by work centers, these loads must be kept within a range (i.e., maximum and minimum values of loads). As a result, before releasing orders to the shop floor, information that describes whether the loads are in the range or not must be known. Melnyk and Ragatz (1988) stated that this information can take several different forms depending on 1. How the workload is shown 2. How the time treated in the load presentations.

1. The load can be stated in terms of total shop load, load by work center, or only for selected work centers (i.e., bottleneck work centers).

2. Treating time in the load presentations can take two forms. In the first form, the information about load presentations can be obtained momentarily at a specific time. In the second form, this information can be obtained per period of time (i.e., shift, week) covering a given time horizon. Information of load presentations can be used as either a type of trigger in a trigger mechanism or a selection rule for managing order release pool.

c) The Planning System: The planning system is mainly responsible for identifying all of the orders which are considered mature and so ready for release to the shop floor. Melnyk and Ragatz (1988) noted that for an order to be mature depends on the type of the planning system. For example in an order-point system, a mature order is any order triggered by inventory falling below the reorder point. In an MRP system, a mature order is one for which the planned-release date has been reached.

The planning system considers mature orders as planned order releases and provides the schedule of the planned order releases to the ORR as information about future demands on shop capacity. The amount of the information that schedule of planned order release provides is called schedule visibility and depends on the type of planning system. For example, in an order-point system, ORR can only be informed by limited information related to orders which are mature as of the current time period. Providing little amount of information to the ORR this kind of planning system's schedule visibility is called as "limited visibility" (i.e., no visibility provided into future loads by such planning systems). On the other hand, in an MRP system, ORR is not only informed of orders which are mature as of the current time period but also of orders that will mature over some given time horizon. In this case, the amount of information given to ORR is extended (i.e., visibility of the schedule is extended). Such kind of schedules has "extended visibility".

Schedule of planned orders can be prepared by controlling the period-to-period capacity feasibility or not. If the schedule is prepared by controlling the period-to-period capacity feasibility it is called controlled schedule. Otherwise, it is called uncontrolled schedule (i.e., the period to period feasibility of the schedule is not evaluated before sending the orders to the order release pool).

d) The Information System: In order to maintain the effectiveness of ORR function, it must be informed by the shop floor and planning system constantly. Melnyk and Ragatz (1988) argued that timeliness and accuracy/completeness are the two measures of the quality of information (i.e., provided by the shop floor and the planning system) that may have an impact on the effectiveness of ORR. Timeliness can be either real time or offline. ORR function is supplied with updated information if the information system operates in real time mode. It is intended that the information system must provide accurate/complete data to maintain ORR function's effectiveness.

3.3. The Role of the ORR

Stevenson et. al (2006) stated that for planning and control purposes, there can be considered to be five stages through which a customer order must pass; 1) Customer enquiry stage, 2) Job entry stage, 3) Job release stage, 4) Priority dispatching, 5) Delivery. These five stages will be explained and the role of ORR in each stage will be emphasized.

3.3.1 Stages of a customer order (Stevenson, 2006)

Customer enquiry stage is the *first decision point* in a job shop environment. In this stage, the decision about acceptance and\or rejection of orders is made. This decision is based on some predetermined conditions, such as current shop load or number of jobs in the PSP. By controlling current shop load between predetermined norms, ORR helps to make decisions about whether to accept or reject orders. In the literature, generally it was assumed that all orders received by the shop in this phase will be accepted, no matter what the shop condition is. This assumption was relaxed by Philipoom et al (1992) and Bergamaschi (1997). According to the relaxed assumption, orders that arrive at a highly congested shop should be rejected immediately or its due date may be negotiated. Actually, at a highly congested shop accepting incoming orders will endanger the ability of the shop to meet due dates. Accepted orders are sent to the *job entry stage*. There is a storage area that consists of all the production orders already processed by the *customer enquiry stage*, but not released yet to the shop. This storage is also called PSP (Bergamaschi et al. 1997), backlog pool (Melnyk et al., 1994), job pool (Irastorza et al., 1974), order pool (Lingayat et al., 1995; Hendry et al., 1994), order release pool (back order pool) (Melnyk et al., 1988; Melnyk et al. 1989). Jobs are waited in PSP until some predetermined job, shop or both job and shop conditions are satisfied. Utilization of PSP will hopefully reduce the level of WIP which facilitates the other SFC activities. In this stage, not only production order preparation is performed, but also the availability of required tooling, personals, machines are controlled. Also, retrieved or defined due date is assigned in this stage. If there is no alternative route in the shop, job routings are determined at this stage. Therefore, this stage is the *second decision point*.

Next stage is *job release stage* in which most of the ORR activities take part. This stage is the *third and virtually the most important decision point* in a job shop environment. Note that, ORR activities can be performed effectively by coordinating job entry stage and job release stage. In this stage, by using any OR mechanism, matured orders are released to the shop floor to be processed. The OR mechanism, named by Ragatz et al. (1988) job releasing function, determines when (i.e, timing convention, triggering mechanism) and which jobs (i.e., selection rule) should be released to the shop floor.

According to Melnyk and Ragatz (1988), PSP is managed by specifying the timing convention, triggering mechanisms and selection rule. The timing convention (either continuous or bucketed) determines when a release can take place (Melnyk and Ragatz, 1988; Bergamaschi et al., 1997). Under the continuous timing convention, a release may occur at any time during the system's operation. Under the bucketed timing convention, releases can occur only at periodic intervals. The triggering mechanism determines within any limits imposed by the timing convention when a release actually should take place (Melnyk and Ragatz, 1988; Melnyk and Ragatz, 1989). In this sense, according to the timing convention utilized (either continuous or bucketed) triggering mechanisms can be either load based or time based. In the time-based triggering mechanism, orders are released to the shop floor according to predetermined time interval and the shop condition does not controlled. On the other hand, in load based triggering mechanism orders are released to the shop floor according to shop or PSP load level. According to PSP based triggering mechanism the decision about when to release a job is based strictly on information about jobs in the PSP while according to shop based triggering, when to release a job is based on current conditions on the shop floor.

Selection rules form the basis for deciding which jobs to release, once a release has been triggered (Melnyk and Ragatz, 1988). Baker (1984a) named the selection rule as the job releasing rule and defined it as a rule which controls the flow from PSP into the shop. Similar to DRs, we can consider selection rules as either local or global. Local selection rules choose the job(s) to be released strictly from information about the jobs in the PSP. On the other hand, global rules consider also information about the shop conditions (i.e., aggregate shop load, load by work center) (Melnyk and Ragatz, 1988). When orders are released to the shop floor, *priority dispatching stage* is started. Priority dispatching stage is the *fourth and the last decision point* in a job shop environment. Orders are processed by using DRs. DRs (Ragatz and Mabert, 1988; Glassey and Resende, 1988; Dessouky and Leachman, 1994; Melnyk et al., 1994) which are also referred as priority rules (Baker, 1984b) select which product(s) to manufacture next at a machine when it becomes idle. When all required operations for an order are processed, it will send to *delivery stage*. If an order entered this stage before predetermined date, this order is called early, whereas if an order entered to this stage after predetermined date this order is called tardy. In the past, only tardiness penalties due to delivery after a promised due date are considered whereas earliness penalties such as storage costs due to insurance, perishing, and bounded capital for the case of a completion of the job before the promised due date, are neglected. Nowadays, tardiness together with earliness penalties are considered in order to meet promised due date thanks to new manufacturing concepts such as just in time (JIT).

3.4. Why Need for ORR?

In recent years, greater product variety and the corresponding shift from build-to-stock to build-to-order production is ongoing trend that increases the significance and also the complexity of order promising. Because build-to-order manufacturers do not build an inventory of standard products, they generally lack the ability to provide promised completion dates to customers that are achievable, tight and computed in real time (i.e. a few seconds or less) for dynamic order arrivals (Moses et al., 2004). However, in such companies, it is essential to quote competitive, yet realistic, lead times for orders. In order to maintain a reputation which will gain further orders, companies must also ensure that such promised delivery dates are met (Hendry and Kingsman, 1991).

Tatsiopoulos and Kingsman (1983) stated that two alternative approaches exist to determine planning values for lead times to use in production planning and control systems. In the first approach the lead times are acknowledged as independent uncontrollable variables. The second approach puts the emphasis on control and attempts to manage the average lead times to pre-determined norms generally known as Input\Output (I\O) control. In the first approach, planning system adopts the planned values for lead times according to the actual lead times as often as necessary. The aim of the planning system is to estimate accurate lead times (i.e., minimize forecasting errors). The authors noted that this approach is responsible for the inflation of lead times reported by Mather and Plossl (1978) as the “lead time syndrome”. However, in the second approach corrective actions are taken on the average lead times to bring them closer to the norms whenever an increase or decrease in actual lead times is observed. Their conclusion was to adopt the second approach which emphasizes I\O control.

I\O control is essentially originated from the relationship among throughput, WIP and MLT which was first shown by Little (1961) and generally known as Little's law. Little's law states that as WIP increases beyond a limiting point, the throughput ceases to increase, while MLT continues to rise. As a result of the Little's law the level of WIP must be kept at a certain level in order to get fairly constant lead times while achieving satisfactory throughput. One of the pioneering works related to I\O control is conducted by Wight (1970). Wight argued that the flow of work both to the shop and within the shop could be controlled in such a way that the size of the queues at each work center in the shop would remain constant which results in fairly constant lead times at the work centers (i.e., as in the second approach). I\O control concept is known as Wight's principle of *workload control* and has been elaborated by many valuable research contributions.

Consequently, in order to get constant (manageable) lead times at work centers the size of the queues at each work center must be controlled. Moreover, in order to control the size of the queues at each work center, the flow of work both to the shop and within the shop should be controlled. The guiding rule behind the controlling of work to the shop is to balance the load released to the shop floor against the available capacity on the shop floor. The control of workload to the shop is handled by the ORR function.

3.5. Related Literature Review

There are plenty of research studies related to ORR in the literature. These studies are summarized chronologically in this section.

Irastorza and Deane (1974) presented an algorithmic procedure for loading and releasing work to a job shop environment. The objective of the procedure was to control and balance of workloads in the shop. Workload balance oriented measures, measures relating to work in process and measures dealing with the ability to meet assigned due dates were three performance measures employed. Significant improvements were obtained through the use of the job pool and the loading algorithm in most balance measures tested as well in work in process related to both total work in the shop and to work performed for jobs in the shop. It could be argued that the reduction of work in process levels was a consequence of the better “balanced” shop because under the improved balance condition there was less interference in the shop, and therefore, a lower in process level was needed to maintain a certain work through put level.

Bertrand (1983) investigated the performance of a workload dependent scheduling and due date assignment rule. Two types of release condition, which were controlled release and uncontrolled release, were compared. Due dates were assigned by using simple (static) and complex (dynamic) assignment rules. Furthermore, additional allowance were used while assigning due dates. These were unconstrained and constrained capacity. Two job sequencing rules were chosen for this study. First one was pure operation due date (ODD) and the other was a rule that combined operation due date information and processing time information. Mean job lateness and standard deviation of lateness were employed in order to compare the results. In addition four way analysis of variance was performed for testing the significance of the effects of the chosen factors. Simulation results showed that the use of capacity constraints generally reduced the variance of lateness. Controlling the workload in the shop seemed to have no direct impact on the variance of the lateness but it seemed to amplify the effect of the sequencing rule and assignment rule. Also, using only time-aggregated workload information had a positive affect on the variance of lateness. In addition, experimental result indicated that, for all three situations considered both due date objectives- a small variance and a constant mean lateness could be obtained simultaneously by selecting appropriate parameters. This research had some managerial implications. Beside these, results showed that the best variance performance was obtained with an assignment rule that used a time phased representation of the workload in the shop, especially in combination with an ODD rule. Researcher concluded that workload control seemed to have no direct impact on the internal due date performance of rules that made use of workload information for setting due dates.

Baker (1984a) examined the impact of job releasing rule on the on scheduling performance. The rule prevented work from being released to the shop while the load in the shop exceeded a given critical level. In this investigation two due date assignment rules; TWK (Total Work Content) and SLK (Equal Slack) and five dispatching rules; ERD (Earliest Release Date), SPT (Shortest Processing Time), MST (Minimum Slack Time), MCR (Minimum Critical Ratio), and MDD (Modified Due Date) were employed. Performance was measured by the average tardiness.

Simulation result revealed that the use and refinement of a job releasing rule was far less important to system performance than was the use of an effective priority scheme. The job releasing rule was counterproductive in conjunction with modified due date priorities because input control removes some options from the set of choices available to a scheduling system.

It was found that job releasing did provide improvements when used in conjunction with such priority rules as minimum critical ratio and shortest processing time because the job releasing rule preempts the pure form of the priority rule to create a hybrid sequencing rule that compensates for some of the shortcomings of pure rule. In addition, a new form of due date assignment rule was investigated but it did not provide any advantage in conjunction with modified due date priorities, although it did lead to improvements in certain other cases. It was observed that the additional parameters required in this new rule were difficult to derive in general. Therefore it was concluded that, even though there appeared to be some advantage exploiting the greater predictability induced by job releasing, a consistent means of implementing this idea analytically did not yet exist.

Onur and Fabrycky (1987) presented a combined input-output system for periodically determining the set of jobs to be released (input variables) and capacities of processing centers (output variables) in the dynamic job shop, so that a composite cost function was minimized. The job shop control problem was mathematically formulated as a 0-1 linear mixed integer program. A hypothetical job shop was simulated for evaluation of the control system.

The performance of the dynamic input output control system (DI/OCS) was compared with the performance of alternative control system that was only input flexibility. Total cost per period, mean flowtime, flowtime variance, mean tardiness, tardiness variance, WIP inventory, and shop utilization were evaluated, as performance measures, under different shop load levels with the FCFS dispatching rule. The simulation results indicated that significant improvements in the overall performance were achieved under highly loaded shop conditions. Significant improvements were achieved for the mean flowtime, flowtime variance, mean tardiness, tardiness variance, and WIP inventory levels. The general improvement achieved implied that the prediction model had some positive effect on performances. As a conclusion the improvements achieved were attributable to the difference in the control systems rather than differences between due date rules.

Melnyk and Ragatz (1988) attempted to narrow the gap between what was being done and what was being researched in order review release (ORR) by examining the ORR mechanism in general and by focusing on the related relationship between it and the dispatching process. They summarized ORR past perspectives, the role of ORR in the shop floor and the components of ORR framework. They concluded that ORR was a diverse process which could contain combinations of lots of factors. So, more research on the full range of ORR environment was needed before reaching any verdict on ORR.

Ragatz and Mabert (1988) extended previous work on job release by providing a controlled comparison, on several dimensions of shop performance, of a broad range of releasing mechanisms in combination with both simple and complex dispatching rules. In this study, five releasing mechanism, namely immediate release (IMM) backward finite loading (BIL), modified infinite loading (MIL), maximum number of jobs (MAX), backward finite loading (BFL) were compared according to average total cost period, mean absolute deviation from due date, mean in shop queue time, mean and maximum number of jobs on the shop floor performance measurements. First come first served (FCFS), shortest processing time (SPT), earliest due date (EDD) and critical ratio (CR) were chosen as dispatching rules. Due dates of a job was assigned by using number of operations under tight, medium and loose condition. In addition, sensitivity analysis was conducted to evaluate the impact of shop cost structure and shop utilization o the performance of releasing mechanism and dispatching rules. Result of this study showed that, the controlled release mechanisms BIL and MIL had positive impacts on total cost performance of shop when used in conjunction with either non due date oriented dispatching rule. The controlled release mechanisms improved total cost performance in conjunction with the due date oriented dispatching rules only when due dates were loose. However, even when due dates were medium or tight, controlled release did not appear to cause any deterioration in performance for due date oriented dispatching rules. Result also revealed that, regardless of due date tightness or the type of dispatching mechanisms used in the shop, controlled release reduced shop congestion. In addition, it was seen that MIL, BIL and BFL mechanisms, which held jobs in the backlog file longest, were most effective at reducing queue waiting time and lateness distribution. Beside this, result showed that MNJ mechanism had the least impact on the shop performance. MIL mechanism was the best overall performer. It is suggested that both information about the characteristics of job and about current shop congestion could be useful in setting releasing dates. It's indicated that controlled job release reduced the difference among the dispatching rules by simplifying the dispatching decision by limiting the number of jobs on the shop floor. Result of the study also indicated that, controlling release of work to the shop floor in a job shop system could substantially improve the performance of the system. As a conclusion an important result of this study was the demonstration that job releasing logic could supplement a simpler dispatching rule and bring its performance closer to that of more complex rules.

Bechte (1988) called workload control as load-oriented manufacturing control. He defined load-oriented manufacturing control as a new solution for job shops producing parts in small lots. The technique of load oriented order release is defined to be the nucleus of load oriented manufacturing control. The author explained the philosophy of load-oriented manufacturing control by a funnel model of job shop which illustrates the flow of orders from their generation to their delivery. The model is divided into the two sections: 'order stock' containing the planned orders, and 'job shop', containing the released orders (work-in-process). Five essential events in the flow of orders through the whole system are given as: 1. Entry (order definition), 2. Release (start of manufacturing flow), 3. Input (arrival at a work center), 4. Output (departure from a work center), 5. Exit (end of manufacturing flow). It is noted that these events depend on various decisions by the control and production personnel requiring effective manufacturing control techniques. For this purpose, load-oriented manufacturing control has a planning system for three planning levels: 1. Order entry and mid-term capacity planning, 2. Order release and short-term capacity planning, 3. Operation sequencing. These events and planning levels are explained throughoutly and a successful implementation of load-oriented manufacturing in plastic leaves factory is given.

Bobrowski and Park (1989) examined the effects of several release mechanisms on the performance of dual constrained job shop. In this study, each of the workers were capable of any workcenter at full efficiency and they completing processing at work centers immediately returned to the central control and moved to the work center with the longest queue length. Due date of jobs were assigned solely on processing time. Processing time of an order was multiplied by allowance factor r and its added to the start time of next scheduled shift. Jobs were released to the shop by using four order release mechanisms, which were immediate release (IMR), backward infinite loading (BIL), maximum shop load (MSL) and forward finite loading (FFL) mechanism. Dispatching in the shop floor was performed two dispatching rules, modified operation due date (MOD) and critical ratio (CR) rule. Primary performance measure of this job shop was total cost per day consisting of inventory holding, late penalty and worker transfer costs. In addition, average lateness, tardiness and proportion tardy for lateness criteria, average waiting time on the shop floor and average time spent in the backlog file were collected. Simulation result showed that BIL and FFL were superior overall and these two releasing mechanism produced shop performance independent of due date setting. Results also revealed that the release mechanism coupled with the priority sequencing rules to form a control system that controlled jobs arrival to departure. Researchers concluded that since worker movement within a dual constrained job shop acted to reduce bottlenecks, the choice of a particular due date oriented priority sequencing rule was less critical than the shop's ability to provide the proper set of jobs to the shop floor in a timely manner.

Bobrowski (1989) developed a model called discrete release model considering the routing, loading, and release decisions as well as the customary sequencing decision evident in most job shop research. The overall strategy for the research was to test the ability of the loading exchange heuristic to improve shop performance when a single pass. The job shop possessed two types of alternate routing capability or shop flexibility. One type of routing consisted on coupling a primary machine with an alternate machine, referred as ALTMACH, and second type of alternate routing considered a complete set of replacement operations done at different machine centers to the primary sequence of machines, referred as ALTSEQ. The jobs were collected in a pre-shop and ordered according to critical ratio. Three levels of shop flexibility (low, medium, high) were chosen. The due dates were set external and set two levels (tight, loose). Two types of routing strategy, minimum last load (MLL) and balanced total load (BL) were utilized. Performance measurement of the research consisted of system cost, which included work in process, finished goods costs and penalty cost for tardiness, as well as total flowtime and flowtime.

Simulation experiments showed that the use of loading exchange heuristic under certain shop conditions provided an improvement in the shop's performance that was statically better than a similar shop that was loaded without the use of heuristic. Despite not showing an improvement for every condition and environment, the limitation was primarily because there was very little system improvement left to be gained. As a conclusion it is seen that the potential for the heuristic was not limited to a shop environment where machine flexibility was available. The heuristic seemed appropriate whenever the arrival pattern had a significant influence on the process of loading and releasing work to shop floor.

Melnyk and Ragatz (1989) identify and present a framework of ORR. Within this framework, they identified issues and topics which must be considered in any study of the ORR function. An attempt has also been made to illustrate the importance of ORR by means of a simple exploratory simulation study. The results of this simulation experiments revealed that the presence of an order release mechanism does have a significant effect on the performance of the production system. But, they noted that the use of order release mechanisms when compared to no order release case resulted in poorer performance in terms of the measures of delivery performance; however the use of them resulted in better performance when evaluated using the WIP and workload balance measures (i.e., the use of order review/release introduced a trade-off between on-time delivery and WIP/workload balance).

The primary concern of the simulation experiment was to evaluate the effect of ORR on the performance of the shop, and to analyze possible interactions between the pool management mechanisms, degree of due date tightness and the dispatching rules on the shop floor. For this purpose, three pool management approaches were considered. The timing convention used throughout was 'continuous' and the selected ORR mechanisms were (1) No order review release, which meant that all orders released from pool upon arrival (NORR), (2) Aggregate workload trigger, work-in-next-queue selection (AGGWNQ), (3) Work center workload trigger, earliest due date selection (WCEDD). Four dispatching rules were use on the shop floor; first come first served (FCFS), shortest processing time (SPT), earliest order due date (EDD), and slack per remaining operation (S/OPN). Due date tightness was examined at four levels (K values of 6 which represented very tight due date, 9, 12 and 15 which represented very loose due date). Six measure of shop performance were collected in the simulation. These measures fell into three categories: measure of delivery performance (mean tardiness and proportion tardy), measures of shop load (mean number of jobs in the shop, mean wait (queue) time in the shop and mean wait time in the system), and measures of shop load (mean of the standard deviations of queue lengths). According to the ANOVA results, they reported that the dispatching rules and the type of the order release mechanism in place had a significant impact on all six measures of system performance while due date tightness was significant for five of the six measures. They also observed numerous significant first-order interactions.

In most measures (i.e., mean jobs in the shop, mean work in pool, mean work in system, and mean of standard deviations of queue lengths), this effect was limited to the interaction between the dispatching rule and ORR mechanism. The first order interaction between due date tightness and dispatching rule was found to be significant only for the two tardiness measures. There found to be no significant interaction between due date tightness and ORR mechanism. One of the conclusions suggested by the simulation experiments was that controlling order release reduced work in process levels in the shop and also reduced variability of the shop load. Another conclusion identified by this study was that while controlling order release may have not reduce the total time an order spent in the system, it could influence where the order spent its time. Under controlled order release, waiting in the order release pool for waiting on the shop floor was substituted.

Hendry and Kingsman (1989) set out the differences between the requirements of make-to-stock (MTS) and make-to-order (MTO) sectors and determined whether the research to date can meet their needs of the MTO sector. For this purpose many different areas are considered, including production scheduling, capacity control, and the setting of delivery dates. They also discussed popular production planning approaches, including MRP II, OPT, and JIT. It is shown that there is a need for more research to provide production planning systems which have been designed specifically for the MTO sector.

Kingsman et al. (1989) extended the ideas to develop a methodology for controlling manufacturing lead times. Contrary to past approaches which have concentrated on scheduling a given set of orders through the shop floor in some optimal fashion to meet their specified delivery dates they adopted a structural approach which includes customers orders planning and job release functions. The basic concepts developed include a hierarchy of backlogs of work responsible for a consequent hierarchy lead

times that add up to the total delivery lead time. Input\output control procedures aim at maintaining the backlogs, and hence lead times, within norms set by management.
Spearman et al. (1990) aimed to develop a system that possessed the benefits of a pull system and could be used in a wide variety of manufacturing environments. They proposed constant work in process (CONWIP) approach which offers to promise their aim. They described a pull based production control strategy that offered the possibility of significant improvements over other production control system. First in system first served (FSFS) queue discipline was used at all process centers. Numerous simulations were conducted in order to make comparison between CONWIP and push based system.

Simulation results revealed that many benefits of CONWIP could be attributed to the fact that it was a pull based production system. The system did offer some distinct advantages over kanban. By allowing WIP to collection in front of the bottleneck, CONWIP could function with lower WIP than kanban. Also, CONWIP made the use of backlog of part numbers, which could allow job sequencing to be done by production personnel.

Hendry and Kingsman (1991a) were being developed a methodology to manage manufacturing lead times in small-to medium-sized make-to-order companies. To be able to achieve this they suggested a hierarchical production planning system in which integration between the production and marketing functions is facilitated. They considered two decision levels: the customer enquiry stage and the job release stage in the hierarchical production planning system. The paper focused on the job release stage by controlling a hierarchical of backlog lengths. At the job release stage the released backlog length for each work center is maintained between predetermined minimum and maximum levels. It is shown that shop floor throughput times- an important part of manufacturing lead times- can be controlled by controlling released backlog lengths. The releasing mechanism is described and it is argued that there can be many benefits of job release including shop congestion, lower work-in-process and lower costs.
Hendry and Kingsman (1991b) developed a decision support system for job release in make-to-order companies which is developed to be a hierarchical system that addresses

two decision levels, the customer enquiry stage and the job release stage. The proposed job release mechanism has two objectives: 1. Controlling shop workloads 2. Controlling manufacturing lead times (MLTs). As the past approaches, shop loads are balanced between work centers and work-in-process levels are maintained at acceptable limits. Controlling MLTs is said to be the new feature of the proposed job release mechanism. Controlling MLTs enabled by including a mechanism to ensure that jobs are not delayed in the pool for an unacceptable length of time and is part of a hierarchical system that controls the pool at the customer enquiry stage. While developing such a DSS the main idea is to enable the production planner to decide which jobs to release in a variety of circumstances. According to the desired control the production planner can use one or more of three types of release mechanisms such as push release, pull release, and also push specific jobs (i.e., expediting purposes). Also, DSS incorporates two capacity adjustment methods- operator reallocation and overtime. They reported that initial responses to the job release DSS in a small subcontracting company have been positive.

Melnyk et al. (1991) stated that most research studies investigating the impact of ORR mechanisms on shop performance have focused strictly on managing the flow of orders to the shop floor once they have been generated by the planning system. Contrary to these studies, in this study authors considered the possibility that the manufacturing planning system may be managing the incoming work flow so that peaks and valleys in the workload have been smoothed out. The governing idea was that such smoothing by the planning system can improve the system performance and enhance the effects of ORR. Thus, primary objective of the study is to examine the effect of smoothing of scheduled workload on the performance of the shop, and to analyze possible interactions between planning system smoothing, ORR, and shop floor dispatching. As a result three experimental factors are examined via seperate analysis of variance on the six system performance measures: 1. work load smoothing 2. order release mechanisms; and 3. dispatching rules.

The first experimental factor (work load smoothing) deals with the way in which the planning system smoothes shop work load. First, the type of the smoothing was determined. In this first stage of the study, the floor and ceiling values are set at the 10th and 90th percentiles of the unsmoothed weekly workload distribution. These limits are combined to create four levels of the smoothing factor: none, floor, ceiling, and both. In the second stage of the study, the degree of smoothing was determined-that is, the specific percentile values chosen for the ceiling and floor. These percentile values are determined to be 0-100, 10-90, 20-80, which are hold for no smoothing, moderate smoothing, and extensive smoothing, respectively. Based on the results of the study, only symmetrical smoothing is considered in the second stage.

The second experimental factor (order release mechanism) focuses on the method used to manage the release of jobs from the order release pool. Two levels are considered for this factor: 1. Immediate Release (IMM) 2. Maximum Load Limit (MAX). The third and the last factor (dispatching rules) deals with scheduling operations at the various work centers on the shop floor. Three levels of this factor was considered: 1. First-Come-First-Served (FCFS) 2. Shortest Processing Time (SPT) 3. Minimum Slack (MinSlk).

The results of the stage one experiment clearly indicate that work load smoothing by the planning system can improve system performance. The results of regarding the effects of the different types of led to the decision to eliminate floor and ceiling only smoothing from consideration in the stage two experiments. The asymmetrical types of smoothing appeared to offer no advantage over smoothing both peaks and valleys in workload. The results of the stage two experiments indicate that as the degree of smoothing increases, there generally is monotone improvement in shop performance. Moreover, the magnitude of the improvement appears to be greater in moving from (10,90) to (20,80) smoothing from (0,100) to (10,90). Apart from the impact of greater degrees of smoothing, the results of the stage two experiments show more clearly than the stage one experiment that the combined effect of work load smoothing by the planning system and controlled release by the ORR system is to dramatically reduce variability in the system. They also reported that the combination of controlled release job release and planning system smoothing reduces the performance difference between MinSlk and the two non-due date oriented dispatching rules.

As a result, the results of the experiments support the governing idea that the effectiveness of ORR can be enhanced by the presence of a planning system that does some coarse smoothing of scheduled workload. Then, the ORR system acts as a finer filter to further stabilize the system. The two filters are complimentary tools for reducing variance in the system-that is, planning system smoothing strongly affects job flow times, while ORR strongly affects work in process levels.

Imtiaz, A. and Fisher, W.W. (1992) investigated the effects of due date assignment, release and sequencing interactions with a simulation model of a dynamic five machine job shop in which early shipments were prohibited. Those combinations of procedures that were most effective were also identified. Due date of a job was assigned by using constant (CON), number of operations (NOP), jobs in queue (JIQ) and jobs in system (JIS) due date assignment rules. Job release was performed by using the following rules: immediate release (IMM), backward infinite loading (BIL), modified infinite loading (MIL) and forward finite loading (FFL). Dispatching was achieved by using first come first served (FCFS), shortest processing time (SPT), earliest due date (EDD) and critical ratio (CR) dispatching rules. Performance of each model was compared according to average total cost (including work in process (WIP) inventory, finished goods inventory and late delivery penalties), average cost per week at other penalty ratios, mean job flowtime (arrival to completion), mean job tardiness, mean absolute deviation from due dates, mean waiting time on the shop floor, and proportion of jobs tardy. In order to test the impact on policy performance of different utilization rates, selected experiments were repeated under both higher and lower utilization levels by varying the mean arrival rate. Results of the study revealed that the combination of rules used in this type of job shop was at least as important as the choice of individual due date, release, and sequencing methods. For most of the performance criteria, a policy combination could not be identified which was superior to others at all utilization levels. Therefore, when selecting particular rules, it would seem advisable to consider the other rules in place as well as expected shop utilization and management’s objectives. Results also showed that, with regard the desirability of controlled versus immediate release, there was no clear winner. IMM performed best in many cases, but it was quite poor in others.

Roderick et al. (1992) investigated the performance of four order release strategies for use in production control. Two of these strategies, the constant work in process (WIP) and the bottleneck strategies, employed characteristic curves, which defined the relationship between WIP and rate of production. A third strategy, which was labeled the INOUT strategy, matched the order releases to completions smoothed over a time horizon. The fourth strategy fixed order release, which was labeled FIXED strategy, to match desired production output target. A technique was developed that allowed the four strategies could be fairly tested statistically. All strategies were simulated over a range of small and large shops, similar and dissimilar routings, normal, exponential and beta processing distributions, all using the earliest due date (EDD) queuing discipline.

In this study, due dates for arriving orders were determined by adding a total lead-time to the current date. All factory models were assumed the same three job types and stable production mix. Average work in process (WIP), percent tardy jobs and throughput were used in order to test the simulation results. By applying the central limit theorem, their study used a conventional one-sided test of hypothesis for mean WIP and mean total throughput.

According to simulation results, under all 12 shop conditions, CONWIP had statistically lower total mean throughput in only large shop with similar routings using normal distribution. For the performance criteria of percent tardy jobs, both the CONWIP and BOTTLE strategies gave superior performances In addition, CONWIP yielded superior performance regardless of performance criteria, size of plant, routing type, or processing distribution included in this research. According to sensitivity analysis, the BOTTLE strategy appeared as a statistical best performer in eight of 12 combinations of production rates and performance criteria with the FIXED strategy appearing in four of the 12. CONWIP was the obvious superior performer for the small shop condition with small shop; similar routings with processing time normally distributed condition for all three levels of production rate and performance measures. Beside this, INOUT would seem to be in peril, since this particular strategy was shown to be a very poor performance under almost all conditions. As a conclusion, under no category of shop size, routing type, or processing distribution did the BOTTLE strategy outperform the CONWIP strategy; however, the BOTTLE strategy was still found to be a strong competitor to the CONWIP strategy under most conditions.

Dessouky and Leachman (1994) focused on the former, release scheduling. A computationally practical integer programming model is proposed for release scheduling, with which simple heuristics such as first-in-first-out (FIFO) can be integrated for dispatching decisions. In computational experiments the proposed model is compared to release scheduling based purely on heuristics and to release scheduling based in part on an approximate linear programming model. In support of release decisions, an optimization model is proposed that is to be resolved periodically or whenever a major change in factory status occurs, such as a major machine failure. In this manner the production starts schedule is updated to reflect the currentfactory status and the current factory demands. First, a linear programming model incorporating time lags to approximately account for processing times is formulated. Although such a model is a somewhat crude approximation, it is computationally practical to solve. Next, a new integer programming model of operational scheduling that precisely accounts for processing times, but restricts the domain of allowed schedules, is formulated. As will be shown, this formulation is such that near-optimal integer solutions are computationally practical to obtain.

Hendry and Wong (1994) investigated whether the conclusions of Melnyk and Ragartz (1989) were correct and hence a rule such as that suggested by Hendry and Kingsman (1991a) could reduce lead times. The simulation experiment carried out by Melnky and Ragartz (1989) was repeated with four versions of Hendry and Kingsman's (1991a) rule included in the analysis. They were aggregate workload trigger, work in next queue selection (AGGWNQ), work centre workload trigger, earliest due date selection (WCEDD), job trigger, shortest slack and work centre workload selection (JSSWC) with four versions namely JSSWC (A), JSSWC (B) JSSW (C) and JSSWC (D). Among these rules only JSSWC rules adjust capacity. The aim was to seek possible explanations for the poor performance of the mechanisms studied in the initial simulation and to ascertain whether an alternative releasing mechanism operating under similar experimental conditions could reduce lead times. The three releasing mechanisms described were compared with a scenario in which no releasing mechanism was in place, this was referred to as NORR in this research. TWK rule was employed in order to assign delivery date for orders. First come first served (FCFS), shortest processing time first (SPT), earliest due date (EDD), slack per remaining operation (S\OPN) and first released first served (FRFS) rules were selected to dispatch order in the shop. ANOVA was used to test whether each of these three experimental factors had a significant effect on the results in simulation. proportion of tardy jobs, mean tardiness (measures of deliver performance), mean number of jobs in the shop, mean wait time in the shop, mean wait time in the system (measures of work load) ,mean of the standard deviation of queue lengths (measure of work load balance) and hours of over time (measure of capacity adjustment) are selected in order to compare the performance of these rules.

Results confirmed the previous research in showing that releasing mechanisms lead to a reduction in the amount of WIP. For most of the rules tested, there seemed to be a trade off that delivery performance worsened as WIP was reduced, except JSSWC (D). The improved performance of the JSSWC (D) rule compared with the other releasing mechanisms was almost certainly due to its increased sophistication. As the RBL value gets larger, JSSWC (D) rule begins behave like NORR.

In conclusion, they had shown that a simplified version of the releasing rule proposed by Hendry and Kingsman (1991a) performed better than other releasing rules under all criteria studied except workload balance. In comparison with no releasing mechanism, this rule improved delivery performance in terms of amount by which late orders were overdue, but not in terms of the proportion of tardy orders. It improved upon no releasing mechanism under all other criteria studied. It could be obviously seen that releasing rules, which were part of a hierarchical planning system and which allowed capacity to be adjusted could improve delivery performance when compared with releasing rules, which did not have these properties.

Melnyk et al. (1994a) evaluated the impact of different job release time distributions on shop performance. Research objectives were; to examine the relationships between alternative distributions for generating job releases and the performance of a simple random job shop; to inspect each family of distributions to identify the characteristics contributing to changes in performance; and to examine the findings in terms of their implications for computer simulations of job shop systems.

Total estimated work content (TWK) approach was used in order to assign due date of a job. Consistent with their objectives, three experimental factors were selected: release time distribution, capacity utilization and dispatching rule. Eight different types of input distributions were considered. They were constant (CON), uniform (UN), normal (NOR), triangular (TR), exponential (EX), bimodal (BM) and gamma distribution. Two levels of capacity utilization, a low level of 78.4% and a higher level 88%, were examined. In addition, two dispatching rules, shortest processing time (SPT) and minimum slack time (MinSlk) were employed. Mean flowtime (MTIME), number of jobs tardy (NTARD), mean tardiness (MTARD), and shop load measured in hours (LOAD) were recorded as performance measures. At each level of utilization, two way analysis of variance (ANOVA) were made and the relationship between system performance and distribution traits were examined by using analyze of covariance (ANCOVA).

Simulation experiments showed that how jobs released to the shop floor had a significant impact on the system performance. Researchers also found that shop performance was significantly affected by the release time distribution of jobs. As a conclusion, researchers told that release time distributions were too important to be ignored and planning system actions was influenced activities on the floor.

Melnyk et al. (1994b) examined the effect of using three different tactics for improving system performance: dispatching, ORR and variance control. By examining all the three sets of tactics simultaneously, this study tried to evaluate how these tactics interacted and how they affected the system performance. Due dates were assigned by using total work content (TWK) rule. The weekly released schedules, the presence of order release mechanism and the distribution of operation processing times were selected as examples of areas where variance could be either created or controlled. First come first served (FCFS), shortest processing time (SPT), minimum slack time (MINSLK), slack per remaining operation (S/OPN) and critical ratio rule (CRR) were employed. A simulation of a simple random job shop was used and the results generated were analyzed using multiple regression. Six measures of shop performance were collected in the simulation. They were mean tardiness, proportion tardy, mean and variance of work in process, mean and variance of flowtime through the system. Simulation result showed that the effectiveness of ORR was potentially dependent on the presence of variance control both at the planning and the shop floor levels. It also reveled that SPT was not necessarily an effective dispatching rule in all settings.

Ashby and Uzsoy (1995) developed a family of scheduling policies for a make –to-order manufacturer operating in a group technology environment. The scheduling policies integrated order release, group scheduling and dispatching heuristics and took into account both order due dates and sequence dependent setup times.

The company under study was a medium sized procedure of air and hydraulic cylinders. The objective of this research was to develop a set of scheduling heuristics for the order dependent components that would allow the company to maintain its due date performance while reducing SDLT (Standard delivery lead time) from seven to three days. In this study, due dates can be set externally by customer or quoted by the company's sales departments by adding the arrival time of an order to its lead time. There were two types of set up time; first one was major setup which referred to the set up time between orders of different diameter, whereas minor setup included the set up time due to tooling and programming changes if two orders of same diameter with different attributes are processed in immediate succession. Release date of an order was calculated by subtracting PLT (Production delivery lead time) from its due date. Orders were grouped and the group processing time for each group was calculated. Releasing of order to the shop floor is performed by using order release heuristic. Four order release rules, pull shortest group processing time (PSGPT) first, pull longest group processing time (PLGPT) first, pull smallest setup cost order – SGPT (PSSS-S) first and pull smallest setup const order- LGPT (PSSC-L) first were employed in order to chose which jobs are released to the shop floor. The processing order of the groups in the schedule was performed by using group sequencing rule, which were longest group processing time (LGPT) first and shortest group processing time (SGPT) first. The processing sequence of orders within a group were achieved by order sequencing rules, which were earliest due date (EDD), shortest processing time (SPT),longest processing time (LPT) and minimum setup time (MST).

Simulation results revealed that the proposed scheduling policies combining order release and group sequencing significantly outperformed the presented system for the number of tardy jobs and performed as well or better for the remaining performance measures. It is also show that any of the four order release rules combined with either EDD or MST order sequencing significantly improved due date performance. Researches confirmed that dispatching rules significantly affected the performance of order release rules and they stressed that order release must be combined with a good sequencing rule to improve due date performance. However, there was no significant difference in performance between the three group sequencing rules.

Lingayat et al. (1995) investigated the use of an order release mechanism (ORM), which is based on controlling the release of orders to the bottleneck machine, for a specified flexible flow system (FFS). Objective of the research was to demonstrate the importance of an ORM as a production control by showing how the use of a carefully developed ORM could improve the system performance. In this investigation due dates were assigned based on lead time. Three dispatching rules, first come first served (FCFS), smallest imminent operation (SIO) and priority to orders which are going to the bottleneck machine. The system performance was compared with no ORM and CONWIP according to selected performance measurements which were; mean and standard deviation of shop factor, mean and standard deviation of system factor, mean and standard deviation of WIP. Simulation results showed that the performance of the system with the ORM was significantly better than the performance of the no ORM. It is also found that ORM reduced the variance of the performance criterion. According to simulation results, researchers concluded that the choice of ORM was important than dispatching at least the FFS.

Wisner (1995) sought to provide researchers with a useful guide to existing opinions and findings with respect to the order release decision, as well as identify some related areas for further research in his review study. According to the author, order release policies can be categorized as either finite loading techniques (orders are released when the shop or machine loadings are less than the desired loadings) or infinite loading techniques (orders are released at a predetermined release date regardless of current shop or machine loadings). He further divided each category into two subcategories. In the first subcategory he described forward loading techniques and in the second subcategory he described backward loading techniques. The author also classified order release research into three sections: 1. descriptive or empirical studies including case and survey research, 2. Analytical or optimization based studies, 3. Studies using simulations of job shops or flow shops to test combinations of release policies and other experimental factors (i.e., dispatching rules). A Table summarizing the models and policies used in the simulation research also included since this research area comprises the bulk of the job release literature. He also briefly described the research studies which investigate the relationship between release and dispatch policies, release and due date policies, release and loading policies, and release and shop utilization levels. His paper concluded with identification of some related areas for future research.

Hendry et al. (1998) designed a simulation model to test the effectiveness of WLC concept on the performance of make-to-order companies, including the control of manufacturing lead times. The paper first presents a discussion of previous research that has examined the effectiveness of WLC systems and gives a more detailed description of the particular WLC concept modeled in the simulation. According to this description, their WLC addresses two major decision levels, the job entry level and the job release level. At the job entry level, customer enquiries are processed, and delivery dates and prices are quoted to customers. At the job release level, decisions are made regarding which jobs should be released to the shop floor so that processing can commence. The simulation model enables the effect of various control parameters within this WLC concept to be explored, including those used at the job entry level to control manufacturing lead times. Experimental results revealed that this particular concept can lead to lower manufacturing lead times when compared with an environment of no control, even when the same total workload is processed by the shop.

Sabuncuoğlu and Karapınar (1999) was performed the first detailed simulation study in which both periodic and continuous ORR methods were compared simultaneously. One of the purposes of this research was to clarify the research paradox about performance of ORR. They believed that the potential benefits of ORR could be realized in research environments if congestion was properly modeled. . They considered the shop with materials handling system and finite buffer capacities, and showed how a load-based release method could improve overall manufacturing lead times. They also proposed a new classification framework by which the existing studies in the literature could be easily classified.

Due date of an order was assigned by using TWK (total work content). Two types of dispatching were made to operate the material handling system: a) selecting a transporter from a set of idle transporters to assign for a request (workstation initiated), and b)selecting a work center from a set of work centers requesting a transporter (vehicle initiated task assignment). For work station initiated task assignment, they used SDS (smallest distance to station) and for vehicle initiated task assignment, they used MOD FCFS (Modified-first-come-first-served) rule. Five continuous; IMR (Immediate release), CAGG (Continuous Aggregate loading), WIBL (Workcenter Information based loading), PBB (Path based bottleneck) and CINF (Continuous infinite loading) and four periodic; IR (Interval release), PAGG (Periodic aggregate loading), PINF (Periodic infinite loading) and FFIN (Forward finite loading) ORR mechanism were tested in the experiments. For each release mechanism, FIFO (First in first out) was used to rank the jobs in the release pool. To dispatch the jobs on the shop floor, SPT (Shortest processing time) and MOD (Modified operation due date) was used in the experiments. Two levels of due-date tightness were considered.

Simulation results were presented for different performance measures such as mean flow time, mean tardiness and mean absolute deviation. The results were also analyzed by ANOVA for statistical significance, considering all factor combinations. Finally, MCP (Multiple Comparison Procedures) was used to rank the ORR methods for each performance measure.

Result showed that overall time in the system could be reduced if congestion on the shop floor was properly modeled. The result also indicated that the due date performances of the system could be improved considerably by an effective ORR mechanism. In addition, it is also found that continuous rules performed well for the flow time and tardiness related criteria whereas periodic rules such as PBB and PAGG showed better performance for the mean absolute deviation criterion. For the MAD criterion, it seemed that a periodic release mechanism with an appropriate period length could produce satisfactory results. Researchers declared that except for MAD, they did not observe any significant interaction between ORR and dispatching. In the MAD case, however, the performance of ORR methods could be improved more by using due date based dispatching rules. The results also indicated that differences in the relative performance of ORR mechanisms became more significant at high utilization rates and with tight due dates. Researchers concluded that the current system load and the job due date information has been very important for the successful implementation of ORR policies.

Bertrand and Van Ooijen (2002) developed a simple model of relationship between workload and effective operation processing times. They have included this model into a classical job shop simulation model in order to investigate the effects of this relationship on the performance of the shop, with and without workload control. The simulation results revealed that contrary to earlier research with conventional job shop models, workload control can have a strong impact on shop output and on work order throughput times. The magnitude of the effect that they observed in the study is in line with the performance improvements reported from implementation of workload control systems in real life production system. They concluded that workload control is a necessary control function for shops that operate at a highly capacity utilization level, have a varying order arrival pattern and for which the effective processing times are affected by the level of the workload.

From the literature, it is seen that WLC concept is elaborated by including stages through which a customer order must pass (i.e. Job entry stage, job release stage etc.) and some decision points (i.e. acceptance/rejection rule, due date assignment rule etc.) in these stages. It is stated that all these stages are interdependent and must be considered simultaneously to improve the shop performance. Also, it is noted that the whole shop can also be protected against external dynamics via high flexibility of the capacity. In this study, a wide range of decision points are simultaneously considered to see whether they improve the shop performance as well as the effectiveness of each decision levels or not. Moreover, apart from the published literature, the effect of stationary PSP size as well as flexibility of the capacity on the effectiveness of the ORR is investigated together.

3.6. Methodology

A computer simulation model of a hypothetical job shop manufacturing system has been used as a test bed for this research. The simulation model was programmed in SIMAN simulation software. All statistical analysis was carried out using SPSS version 15. In all cases, $\alpha=0.05$ was used in evaluating statistical significance. The discussion of the research methodology is presented in eight sections. In the first section, the major features of the simulation model are given. In subsequent sections, how acceptance/rejection decision is made, due date assignment model, OR mechanisms, measures of performance, the experimentation strategy, the experimental factors, and the experimental design is discussed.

3.6.1 The Simulation model

The shop consists of ten work centers. Each work center contains a single machine and can process only one order at a time. No preemption is permitted. Job routings are random, with revisits to a work center. The number of operations per an order is uniformly distributed between one and ten, and operation processing times are drawn from a uniform distribution at each machine (in time units). Three different shops with different levels of flexibility are considered to measure the effect of the degree of flexibility (DF) on shop performance. The parameters of uniform distribution from where operation processing times for each work center are drawn are given in Table 3.1, Table 3.2, and Table 3.3 in increasing order of the DF of the shop. Note that, with processing capabilities represented by Table 3.1 each operation of an order can only be processed at a certain machine in a work center at a time. Thus, the DF of the shop is considered to be zero which means the shop has no flexibility. With processing capabilities represented by Table 3.2 it is seen that each operation of an order can be processed at one of the two alternative machines. Thus, the DF of the shop is considered to be one which means the shop has a 1 DF. Thus, with processing capabilities represented by Table 3.3, the shop has a 2 DF. Orders arrive according to an exponential distribution with a mean of 2 time units.

Table 3.1. Operation processing times for each WC (DF=0)

Operation No	The Range of Operation Processing times for each Work Center									
	1	2	3	4	5	6	7	8	9	10
1	(2,8)									
2		(1,5)								
3			(2,10)							
4				(1,6)						
5					(1,4)					
6						(1,7)				
7							(1,9)			
8								(1,7)		
9									(1,5)	
10										(1,6)

Table 3.2. Operation processing times for each WC (DF=1)

Operation No	The range of Operation Processing times for each Work Center									
	1	2	3	4	5	6	7	8	9	10
1	(2,8)	(2,8)								
2		(1,5)	(1,5)							
3			(2,10)	(2,10)						
4				(1,6)	(1,6)					
5					(1,4)	(1,4)				
6						(1,7)	(1,7)			
7							(1,9)	(1,9)		
8								(1,7)	(1,7)	
9									(1,5)	(1,5)
10	(1,6)									(1,6)

Table 3.3. Operation processing times for each WC (DF=2)

Operation No	The range of Operation Processing times for each Work Center									
	1	2	3	4	5	6	7	8	9	10
1	(2,8)	(2,8)	(2,8)							
2		(1,5)	(1,5)	(1,5)						
3			(2,10)	(2,10)	(2,10)					
4				(1,6)	(1,6)	(1,6)				
5					(1,4)	(1,4)	(1,4)			
6						(1,7)	(1,7)	(1,7)		
7							(1,9)	(1,9)	(1,9)	
8								(1,7)	(1,7)	(1,7)
9	(1,5)								(1,5)	(1,5)
10	(1,6)	(1,6)								(1,6)

The assumptions of the simulation model

- Orders are coming directly from the customers and the accepted orders are manufactured and shipped to the customer directly.
- Each order consists of only one job.
- Order arrivals occur according to exponential interarrival time distribution at any time and the order batch size is considered to be 1.
- The product mix as well as the process plan of a particular order type varies and not known beforehand (i.e., each order can have up to 10 operation, so 10! orders can be processed).
- Orders released from PSP one at a time. But, when a release triggered the total number of orders to be released is decided by the OR mechanism’s logic.
- Each machine can perform only one operation at a time on any order.
- Each order can be processed only by one machine at a time.
- An operation on any job can not be performed until all previous operations of the job are completed.
- Transportation time between two consecutive work centers is deterministic and assumed to be 3 time units. Also, it is assumed that the orders are delivered to customers immediately at the completion time of its last operation. These transformation times are valid for all shop types (i.e., all levels of DF) considered.
- Set-up times are assumed to be negligible.
- There is no interruption, each machine is assumed to be continuously available.

3.6.2 Acceptance/rejection decisions

The preliminary studies related to WLC in a job shop issues that workload in the shop is controlled at the order release stage. Melnyk and Ragatz (1989) show that some releasing rules can result in increased lead times when compared to an environment where all jobs are released as soon as their materials are available. They suggest that the reason for this poor performance is that many of the rules studied only control into the factory; they do not simultaneously control output in terms of capacity. In addition, there is no attempt to control the PSP itself by the use of appropriate decision rules at the job entry level. However, the job release stage can itself only be fully effective if the queue of jobs in the pool is also controlled (Hendry et al., 1998). This means that decisions on workload should be made earlier, at the stage of customer enquiry stage. Thus, in the *customer enquiry stage*, the decision about acceptance/rejection should be made to control the PSP itself.

Acceptance/rejection decision is a task of planning system which is affected by ORR function implicitly. Planning system smoothing procedures, which are excellently issued by Melnyk et al. (1991), can help to make this decision efficiently. Other than these procedures, numerous sophisticated acceptance/rejection techniques are proposed in the literature (Philipoom and Fry (1992), ten Kate (1994), Wester et al. (1992), Wang et al. (1994), Wouters (1997), Raaymakers et al. (2000a, 2000b), Enns (2000), Enns and Costa (2002), Nandi and Rogers (2003, 2004)). All these studies agree with that acceptance/rejection is an active research area. Thus, acceptance/rejection is a topic suitable for further study.

In this study, order acceptance/rejection decision is treated in a simplified fashion. In the *customer enquiry stage* acceptance/rejection decision of an order is based on the current number of jobs in the PSP. Whenever an acceptance\rejection decision of an order is to be made, the current number of jobs in the PSP is evaluated to determine whether it is exceeds or less than the predetermined maximum number of jobs allowed in the PSP (i.e., 1000 jobs). Hereafter this decision variable will be called as PSP size. If the total number of orders in the PSP exceeds predetermined PSP size it is rejected. Otherwise, it is accepted and placed in the PSP as a matured order. Note that the decision whether the order will be accepted or not is made immediately after the arrival of the order. No further negotiation, on price or due date is considered in the current research.

3.6.3 Due date assignment model

The due date assignment is advocated as one of the most important elements in production control. Because product or service delivery systems are not capable of successfully achieving an arbitrary set of due dates, the reasonableness of assigned due dates directly affects due date performance (i.e., delivery reliability and delivery speed) (Vig and Dooley, 1991).

Tsai, C. –H., et al. (1997) stated that integrating the order release control method with due date assignment rules will significantly enhance not only the accuracy of flowtime estimation, but also the performance of due date assignment rules. For this reason, in chapter 2 first a different computer simulation model of a job shop where I/O control is not utilized is constructed. The main reason for this idea is to find the best due date assignment model in the worst case (i.e., where no I/O control is utilized) and in this way we will be sure that it will perform the best in all other cases (e.g., in a controlled job shop). In fact, this is a requirement for our experiments in which controlled and uncontrolled job shop models are tested together with. Hence, we will be able to utilize the best due date assignment model of the worst case (i.e., uncontrolled job shop) in all our computer simulation models with no doubt.

For this purpose, different simulation models are developed (i.e., which do not include control mechanisms) and comparisons of the proposed due date assignment models (*PDDAM)* and conventional due date assignment models (*CDDAM*) from the literature are made in terms of the mean absolute percent error (*MAPE*), mean percent error (*MPE*) and mean tardiness (*MT*). The background information and the components of the present work are explained in the Chapter 2. In Chapter 2, detailed discussion of this preliminary study, results and conclusions can be found. Preliminary simulation experiments showed that for many test conditions, *PDDAM* dominates *CDDAM*. Among the proposed DDAMs adaptive rate exponential rate smoothing (ADRES) is found to be the best for due date performances. Thus, in this chapter ADRES DDAM is used in comparative analysis.

3.6.4 Order release mechanisms

The set of criteria used to determine which orders are released each time that the PSP is inspected, is termed the ‘release mechanism’. It can be classified into five groups: (1) naive rules which exercise little if any control on job release; (2) rules based on information about a particular order such as the delivery date or the number of job operations; (3) rules based on shop information such as total work hours of work already released or the total number of jobs released; (4) rules based on both order and shop information; and (5) finite loading rules which load jobs onto limited machine capacity (Hendry et al., 1994).

Each mechanism has a ‘trigger’ which defines when the PSP should be inspected to see whether future jobs should be released and ‘selection’ criteria to determine which jobs to be released once the trigger has been activated. In this study, aggregate workload trigger, work in next queue selection (AGGWNQ) and work center workload trigger (WCWT) OR mechanisms which are proven to be efficient in terms of many shop performance measures are used. Below, definitions of selected OR mechanisms given.

1) Immediate Release (IMR): Orders are released to the shop as soon as they arrive to the shop (i.e., no control is exercised). Hence, this mechanism’s sophistication level is called naive. In job shop literature this mechanism is often used as benchmark (i.e., no ORR case) in comparisons. Although being a naive rule, it improves some performance measures under some conditions which leaves ORR function at the center of a controversy.

2) Aggregate workload trigger, work in the next queue selection (AGGWNQ): This is one of the release mechanism discussed by Melnyk and Ragartz (1989). The aim of this rule is to ensure that there is enough work in shop as a whole. Rather than inspecting the PSP at regular intervals, a trigger to carry out this task comes into force when the total workload falls to a predetermined level. Once triggered, the mechanism selects the work center with the smallest queue in terms of hours of work and releases an order whose first operation is at that center. In its original version, if more than one order could be released at a specific time, the order with shortest processing time is chosen. If there are two orders with equal processing time, then a 'first come first served' rule operates. In this study, this rule is a bit modified in such a manner that if more than one order could be released at a specific time then only 'first come first served' rule is applied. One order is released at a time until the total shop workload increases above the predetermined level or there are no orders left in the PSP.

3) Work centre workload trigger (WCWT): This is the second rule discussed by Melnyk and Ragartz (1989). It uses each work center workload information and order due dates. It is triggered if there is less than a preset amount of work waiting to be processed at any one work centre and there are orders in the PSP. Once triggered, it selects an order with its first operation at the underloaded work centre. If there is more than one such order, then the order with the earliest due date is selected. If there is still a tie, the first come first serve' rule is applied. In this study, this rule is a bit modified in such a manner that if more than one order could be released at a specific time then only 'first come first served' rule is applied. The mechanism continues to release orders until the PSP becomes empty or until the number of hours of work queuing at each work centre is greater than the preset level.

3.6.5 Shop performance measures

Mainly eleven measures of shop performance are collected in simulation experiments. These measures fall into four categories:

1. Delivery related measures: Mean Absolute Percentage Error (MAPE), Mean Percentage Error (MPE), Average Tardiness (AT), Average Earliness (AE), Proportion of Tardy Jobs (T (%)), Proportion of Early Jobs (E (%))), Completion time of 18000 orders or by other words Makespan (M).
2. Rejection related measures: Total number of rejected orders (R).
3. Flowtime related measures: Shop floor throughput time (SFTT), Manufacturing Lead Time (MLT).

4. Queue related measures: Average total queue waiting time (AQWT), average PSP waiting time (APWT), and Average Queue length of each work center.

3.6.6 The experimentation strategy

In this chapter, two stage strategy is considered to investigate the impact of the experimental factors (i.e., workload smoothing, OR mechanisms, flexibility of the manufacturing system, dispatching rules) on the shop performance. In the first stage, the study focuses on determining an appropriate workload level for each order release mechanism considered (i.e., AGGWNQ, WCWT). Note that, immediate release is not considered which does not take any level of workload into account due to its operating logic. The main question in this stage of the study is that what levels of order release mechanisms should be used to improve shop performance. The output of this stage (i.e., the workload levels of both OR mechanisms) will be used in the second stage as a triggering point for each OR mechanisms, separately.

In the second stage, the study focuses on the whole factor effects on the shop performance considered.

3.6.7 The experimental factors

The primary focus of this study is to analyze possible interactions between planning system smoothing, OR mechanisms, flexibility of the system, and shop floor dispatching rules in a multistage job shop. As a result, four experimental factors are examined via separate analysis of variance on mainly nine performance measures (i.e., MAPE, MLT, SFTT, APWT, AT, AQWT, T (%), M, R):

- Workload smoothing (PSP size),
- Order release mechanisms (OR Mechanisms),
- Degree of the flexibility of the shop (DF),
- Dispatching rules used on the shop floor (DR),

Work load smoothing deals with the way in which the planning system smoothes shop work load. As mentioned in the sub-section 3.6.2 planning system smoothes shop work load according to the size of the PSP (PSP size). Three levels of PSP size factor is determined to measure the effect of this factor on the shop performance. Predetermined levels of the PSP size factor are given in Table 3.4. For example, according to the Table 3.4 first level of the PSP size is 1000 which means planning system allows a maximum number of 1000 jobs in the PSP to be considered as matured orders at any time. Planning system considers this value to decide whether accept or reject the incoming jobs at any time. If there are already 1000 jobs in the PSP upon an arrival of a new order, the planning system rejects this order. Otherwise, the order is placed in the PSP as a matured order where it awaits to be released to the shop floor.

OR mechanisms are the second factor to examine the effect of ORR function on the performance of the shop. Three mechanisms used to manage the release of orders from the PSP to the shop floor are determined to be IMR, AGGWNQ, and WCWT (see Table 3.4).

DF means that whether an operation have alternative machine(s) to be processed or not. In this study, the concern is the DF and its effect on the shop performance. The DF considered to have three levels and explained as follows:

- *Degree 0*: If an operation of an order can only be processed on a certain machine at any time DF is considered to be 0.
- *Degree 1*: If an operation of an order can be processed on one of the two alternative machines at any time DF is considered to be 1.
- *Degree 2*: If an operation of an order can be processed on one of the three alternative machines at any time DF is considered to be 2.

Dispatching rules (DR), are used in scheduling operations at the various work centers on the shop floor and the PSP. Three levels of this factor are considered to be FIFO, EDD, and SPT. The definitions of the DR can be found in chapter 2.

Table 3.4. Levels of the Experimental Factors

Factors	Levels	Range of Variables					
		Low Level		Intermediate Level		High Level	
		Natural	Coded	Natural	Coded	Natural	Coded
PSP Size*	3	1000	1	2000	2	3000	3
Work Load Level (WLL)**	3 for AGGWNQ	500	1	1000	2	1500	3
	3 for WCWT	50	1	100	2	150	3
OR Mec.	3	IMR	1	AGGWNQ	2	WCWT	3
DF	3	0	1	1	2	2	3
DR	3	FIFO	1	EDD	2	SPT	3

*Each level stands for maximum number of orders allowed to be placed in PSP

**Each level stands for triggering points for each OR mechanism. For example, 500 with AGGWNQ OR mechanism means that if total work content of the shop drops below 500 time units then release an order from PSP to shop floor.

3.6.8. Experimental design

For the first stage experiments, a full factorial design is used with 162 cells (i.e., 3x2x3x3x3 which are hold for different levels of PSP size, AGGWNQ and WCWT OR mechanisms, DF, DR, and WLL, respectively) and 10 observations per cell. Here, the aim is to determine the most appropriate WLL of each OR mechanism. While determining these values mainly WIP levels in front of each work center, MAPE, MPE, MLT, SFTT, APWT, AT, AQWT, %T, M, and R performance measures are considered. Other than these, average Lateness (L), standard deviation of lateness (STD. L), and E% performance measures are also reported.

The second stage requires a full factorial design of 81 cells (i.e., 3x3x3x3 which are hold for different levels of PSP size, OR mechanisms, DF, and DR, respectively), 10 observations per cell. To generate the observations for one cell, the simulation model is run until a total of 18000 job completions are collected. After preliminary runs, it is concluded that the statistics belong to first 5000 time units should be discarded to eliminate any starting conditions by using graphical procedure for each performance measure. To reduce variance, common random number streams are used.

3.7. Discussion of the Results

In this section, first the results of the first stage experiments are discussed and the workload levels of both AGGWNQ and WCWT OR mechanisms are determined according to stage one results. Then, the second stage results are obtained by using these work load levels for each OR mechanism together with IMR OR mechanism.

3.7.1. Stage one results

As mentioned in section 3.6.8, first an appropriate WLL for both AGGWNQ and WCWT OR mechanisms are determined. For this purpose, in the first stage a full factorial design is used with 162 cells. Each cell contains an average of 10 observations. The WIP level results with both OR mechanisms are summarized in Table A.5-A.10 in appendix A according to increasing order of DF, respectively. The effects of the selected levels of workload with both OR mechanism on other performance measures summarized according to in increasing order of the degree of flexibility in Table A.11-A.16. Also, comprehensive analyses of these Tables are included in appendix A. Consequently, stage one experiments revealed that the best WLLs for AGGWNQ and WCWT OR mechanism should be 500 and 50 work hours, respectively.

3.7.2. Stage two results

The aim of the first experimentation strategy is to determine appropriate levels of WLL for both AGGWNQ and WCWT OR mechanisms. Stage one results revealed that for both OR mechanisms the low level of WLL gives satisfactory shop performance. Consequently, in second experimentation strategy WLL of AGGWNQ and WCWT OR mechanisms is set to 500 and 50 time units, respectively. Then, in second stage experiments both OR mechanisms together with IMR were compared under different levels of DF, PSP size, DR factors. The resulting measures of performances are given in Tables 3.5-3.7 according to DF, respectively. The main of aim of this comparison is to asses the performances of OR mechanisms under different levels of DF with respect to selected performance measures. However, the main and interaction effects of all factors will be discussed for each performance measure, separately. In all cases, α=0,05 was used in evaluating statistical significance.

Table 3.5. Stage two Resulting Measures of Performances at Low DF

OR mec.	DF	PSP Size	DR	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
IMR	0	1000	FIFO	24	18	6248	6245	0	1919	2802	2227	-15	1409	86	14	54120	0
AGGF				24	02	2465	349	2159	1249	5174	2489	-165	48	53	47	60218	9102
WCEDD				22	07	2361	235	2146	1347	5508	2264	-176	27	62	38	60196	9115
IMR			EDD	44	-02	4919	4919	0	1471	2002	1984	-76	924	75	25	50602	0
AGGF				50	-24	2441	348	2098	1144	4694	2690	-151	48	46	54	59642	8831
WCEDD				41	-16	2355	227	2141	1335	5562	2972	-142	26	47	53	60610	9464
IMR			SPT	380	-358	349	349	0	-211	2467	759	-590	53	28	72	50358	0
AGGF				181	-152	2343	257	2114	1111	5731	3620	-542	32	40	60	59809	8912
WCEDD				124	-94	2333	204	2146	1357	6146	3616	-366	22	43	57	60653	9456
IMR		2000	FIFO	25	17	6294	6285	61	1920	2809	2231	-19	1398	86	14	54005	0
AGGF				24	02	3145	339	2831	1000	5420	2304	-518	47	54	46	56192	6051
WCEDD				20	03	2623	378	2261	749	5028	1690	-526	53	58	42	55740	5926
IMR			EDD	44	-02	4919	4919	0	1471	2002	1984	-76	924	75	25	50602	0
AGGF				75	-50	2929	337	2610	846	5110	2745	-430	46	40	60	56022	6006
WCEDD				62	-43	2507	386	2137	676	5083	2497	-394	55	37	63	55904	6072
IMR			SPT	380	-358	349	349	0	-211	2467	759	-590	53	28	72	50358	0
AGGF				165	-137	2819	267	2578	696	5893	3036	-857	34	40	60	56089	5895
WCEDD				202	-176	2568	304	2280	686	6158	3104	-787	40	38	62	55718	5863
IMR		3000	FIFO	25	17	6294	6285	0	1920	2809	2231	-19	1398	86	14	54005	0
AGGF				25	06	3974	330	3686	1432	5401	2597	-321	45	60	40	55334	4666
WCEDD				18	07	3380	591	2825	917	3997	1641	-323	92	63	37	54255	4146
IMR			EDD	44	-02	4919	4919	0	1471	2002	1984	-76	924	75	25	50602	0
AGGF				54	-21	3792	329	3531	1317	5030	2539	-256	45	56	44	55357	4645
WCEDD				50	-24	3281	553	2765	806	3705	1889	-300	86	51	49	54358	4267
IMR			SPT	380	-358	349	349	0	-211	2467	759	-590	53	28	72	50358	0
AGGF				159	-126	3832	270	3602	1197	5930	3261	-743	34	48	52	55259	4572
WCEDD				301	-273	3118	422	2720	671	5460	2821	-898	62	42	58	54177	4034

Table 3.6. Stage two Resulting Measures of Performances at Intermediate DF

OR Mec.	DF	PSP Size	DR	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
IMR	1	1000	FIFO	09	06	2600	2600	0	218	292	288	-64	506	80	20	45232	0
AGGF				20	05	1681	339	1359	265	680	474	-106	47	64	36	44064	685
WCEDD				19	05	1703	384	1336	270	688	477	-107	55	65	35	43992	668
IMR			EDD	129	-128	1464	1464	0	-271	198	17	-274	261	01	99	43412	0
AGGF				67	-57	1508	328	1192	27	670	695	-194	45	26	74	43968	501
WCEDD				64	-53	1635	368	1279	58	583	547	-175	53	32	68	43987	579
IMR			SPT	194	-105	1038	1038	0	491	2086	1107	-735	182	66	34	44427	0
AGGF				184	-151	1508	267	1253	92	2853	957	-698	34	48	52	44016	679
WCEDD				234	-199	1387	289	1110	140	3096	1115	-723	38	47	53	44005	560
IMR		2000	FIFO	09	06	2600	2600	0	218	292	288	-64	506	80	20	45232	0
AGGF				20	07	1797	338	1477	350	807	570	-100	47	67	33	43988	0
WCEDD				20	07	1803	391	1436	359	818	579	-93	56	67	33	43948	0
IMR			EDD	129	-128	1464	1464	0	-271	198	17	-274	261	01	99	43412	0
AGGF				60	-49	1574	327	1258	80	696	713	-171	45	30	70	43865	0
WCEDD				58	-45	1702	373	1341	114	671	567	-152	53	38	62	43943	0
IMR			SPT	194	-105	1038	1038	0	491	2086	1107	-735	182	66	34	44427	0
AGGF				172	-137	1549	263	1302	167	2941	1042	-705	33	50	50	43989	5
WCEDD				208	-172	1318	279	1050	161	2848	1043	-674	36	49	51	44012	0
IMR		3000	FIFO	09	06	2600	2600	0	218	292	288	-64	506	80	20	45232	0
AGGF				20	07	1797	338	1477	350	807	570	-100	47	67	33	43988	0
WCEDD				20	07	1803	391	1436	359	818	579	-93	56	67	33	43948	0
IMR			EDD	129	-128	1464	1464	0	-271	198	17	-274	261	01	99	43412	0
AGGF				60	-49	1574	327	1258	80	696	713	-171	45	30	70	43865	0
WCEDD				58	-45	1702	373	1341	114	671	567	-152	53	38	62	43943	0
IMR			SPT	194	-105	1038	1038	0	491	2086	1107	-735	182	66	34	44427	0
AGGF				172	-137	1548	262	1301	167	2940	1041	-705	33	50	50	43988	0
WCEDD				208	-172	1318	279	1050	161	2848	1043	-674	36	49	51	44012	0

Table 3.7. Stage two Resulting Measures of Performances at High DF

OR Mec.	DF	PSP Size	DR	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
IMR	2	1000	FIFO	10	06	2629	2629	0	220	307	303	-76	510	78	22	45328	0
AGGF				19	06	1793	341	1467	186	441	364	-159	47	66	34	44046	661
WCEDD				22	05	1576	407	1185	200	497	384	-159	59	66	34	43483	308
IMR			EDD	151	-151	1425	1425	0	-336	267	11	-340	255	01	99	43472	0
AGGF				56	-45	1695	330	1382	-60	456	406	-259	46	30	70	43987	523
WCEDD				61	-47	1709	380	1347	-46	529	457	-268	55	31	69	44035	533
IMR			SPT	169	-56	1268	1268	0	739	2327	1262	-1026	227	77	23	44432	0
AGGF				149	-114	1534	254	1294	85	3007	835	-738	31	52	48	43953	626
WCEDD				192	-152	1537	281	1269	96	3083	849	-822	36	55	45	43984	635
IMR		2000	FIFO	10	06	2629	2629	0	220	307	303	-76	510	78	22	45328	0
AGGF				18	08	2000	342	1685	253	472	416	-145	47	71	29	44059	0
WCEDD				22	06	1616	408	1232	229	523	408	-151	59	68	32	43459	0
IMR			EDD	151	-151	1425	1425	0	-336	267	11	-340	255	01	99	43472	0
AGGF				49	-37	1843	332	1532	-5	438	380	-228	46	38	62	44009	0
WCEDD				55	-41	1854	383	1492	9	511	439	-237	55	38	62	44037	0
IMR			SPT	169	-56	1268	1268	0	739	2327	1262	-1026	227	77	23	44432	0
AGGF				146	-109	1573	254	1335	188	3058	963	-728	31	54	46	43987	0
WCEDD				173	-132	1620	277	1357	153	3034	871	-810	36	57	43	43976	8
IMR		3000	FIFO	10	06	2629	2629	0	220	307	303	-76	510	78	22	45328	0
AGGF				18	08	2000	342	1685	253	472	416	-145	47	71	29	44059	0
WCEDD				22	06	1616	408	1232	229	523	408	-151	59	68	32	43459	0
IMR			EDD	151	-151	1425	1425	0	-336	267	11	-340	255	01	99	43472	0
AGGF				49	-37	1843	332	1532	-5	438	380	-228	46	38	62	44009	0
WCEDD				55	-41	1854	383	1492	9	511	439	-237	55	38	62	44037	0
IMR			SPT	169	-56	1268	1268	0	739	2327	1262	-1026	227	77	23	44432	0
AGGF				146	-109	1573	254	1335	188	3058	963	-728	31	54	46	43987	0
WCEDD				173	-132	1617	277	1355	153	3023	869	-807	36	57	43	43971	0

3.7.2.1. The main and interaction effects of factors on MAPE

From Table 3.8, it is seen that all main factors and their interactions have significant effect on MAPE performance. In Tables 3.9-3.12 pairwise comparisons of main factors are given. From Table 3.9, it is seen that the mean difference of the levels of OR mechanisms is significant. Also, WCWT OR mechanism performs the best MAPE performance. From Table 3.10, it is seen that the mean difference of the levels of the DF is significant. Also, the best MAPE performance is achieved when DF is set to its high level. From Table 3.11, it is seen that the mean difference of the low and the intermediate level of the PSP size is insignificant. Nevertheless, the mean difference of the high and the other levels of PSP size are significant. However, the best MAPE performance is achieved when the low level of PSP size is used. From Table 3.12, it is seen that the mean difference of the levels of the DR is significant. Also, the best MAPE performance is achieved when FIFO dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the MAPE performance of the shop.

Table 3.8. ANOVA results for MAPE

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	656,80[(a)]	80	8,210	272,97	,000
Intercept	825,26	1	825,26	27438,74	,000
ORMec	34,35	2	17,17	571,01	,000
Flexibility	2,75	2	1,38	45,78	,000
PSPSize	1,31	2	,65	21,71	,000
DR	466,50	2	233,25	7755,17	,000
ORMec * Flexibility	5,80	4	1,45	48,19	,000
ORMec * PSPSize	1,60	4	,40	13,34	,000
Flexibility * PSPSize	1,99	4	,50	16,60	,000
ORMec * Flexibility * PSPSize	6,80	8	,85	28,25	,000
ORMec * DR	14,03	4	3,51	116,64	,000
Flexibility * DR	40,88	4	10,22	339,79	,000
ORMec * Flexibility * DR	58,08	8	7,26	241,36	,000
PSPSize * DR	1,27	4	,32	10,59	,000
ORMec * PSPSize * DR	5,02	8	,63	20,85	,000
Flexibility * PSPSize * DR	6,02	8	,75	25,03	,000
ORMec * Flexibility * PSPSize * DR	10,40	16	,65	21,60	,000
Error	21,93	729	,03		
Total	1503,98	810			
Corrected Total	678,72	809			

a R Squared = ,968 (Adjusted R Squared = ,964)

Table 3.9. Pairwise Comparisons of OR Mechanisms in terms of MAPE

(I) ORMec	*(J) ORMec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference[(a)]*	
					Upper Bound	*Lower Bound*
1,00	2,00	,484[(*)]	,015	,000	,455	,514
	3,00	,364[(*)]	,015	,000	,335	,393
2,00	1,00	-,484[(*)]	,015	,000	-,514	-,455
	3,00	-,120[(*)]	,015	,000	-,150	-,091
3,00	1,00	-,364[(*)]	,015	,000	-,393	-,335
	2,00	,120[(*)]	,015	,000	,091	,150

* The mean difference is significant at the ,05 level.

Table 3.10. Pairwise Comparisons of DF in terms of MAPE

(I) DF	*(J) DF*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*[a]	
					Upper Bound	*Lower Bound*
1,00	2,00	,105(*)	,015	,000	,075	,134
	3,00	,136(*)	,015	,000	,107	,166
2,00	1,00	-,105(*)	,015	,000	-,134	-,075
	3,00	,032(*)	,015	,034	,002	,061
3,00	1,00	-,136(*)	,015	,000	-,166	-,107
	2,00	-,032(*)	,015	,034	-,061	-,002

* The mean difference is significant at the ,05 level.

Table 3.11. Pairwise Comparisons of PSPSize in terms of MAPE

(I) PSPSize	*(J) PSPSize*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*[a]	
					Upper Bound	*Lower Bound*
1,00	2,00	-,008	,015	,595	-,037	,021
	3,00	-,089(*)	,015	,000	-,118	-,060
2,00	1,00	,008	,015	,595	-,021	,037
	3,00	-,081(*)	,015	,000	-,110	-,052
3,00	1,00	,089(*)	,015	,000	,060	,118
	2,00	,081(*)	,015	,000	,052	,110

* The mean difference is significant at the ,05 level.

Table 3.12. Pairwise Comparisons of DR in terms of MAPE

(I) DR	*(J) DR*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*[a]	
					Upper Bound	*Lower Bound*
1,00	2,00	-,492(*)	,015	,000	-,521	-,463
	3,00	-1,798(*)	,015	,000	-1,828	-1,769
2,00	1,00	,492(*)	,015	,000	,463	,521
	3,00	-1,306(*)	,015	,000	-1,336	-1,277
3,00	1,00	1,798(*)	,015	,000	1,769	1,828
	2,00	1,306(*)	,015	,000	1,277	1,336

* The mean difference is significant at the ,05 level.

3.7.2.2. The main and interaction effects of factors on MLT

From Table 3.13, it is seen that all main factors and some factor interactions have significant effect on MLT performance. PSPSize*DR, ORMec*PSPSize*DR, Flexibility*PSPSize*DR, ORMec*Flexibility*PSPSize*DR factor interactions have no significant effect on MLT performance. In Tables 3.14-3.17 pairwise comparisons of main factors are given. From Table 3.14 it is seen that the mean difference of the levels of OR mechanisms is significant. Also, WCWT OR mechanism performs the best MLT performance. From Table 3.15 it is seen that the mean difference of the levels of DF is significant. Also, the best MLT performance is achieved at intermediate DF. From Table 3.16 it is seen that the mean difference of the levels of the PSP size is significant. Also, the best MLT performance is achieved when the PSP Size is set to 1000. From Table 3.17 it is seen that the mean difference of the levels of the DR is significant. Also, the best MLT performance is achieved when FIFO dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the MLT performance of the shop.

Table 3.13. ANOVA results for MLT

Source	Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1190914761,56[a]	80	14886434,52	488,98	,000
Intercept	3908577122,29	1	3908577122,291	128386,04	,000
ORMec	27491837,93	2	13745918,97	451,52	,000
DF	424267207,60	2	212133603,8	6968,01	,000
PSPSize	12296013,15	2	6148006,573	201,95	,000
DR	175386680,13	2	87693340,07	2880,49	,000
ORMec*DF	32996770,34	4	8249192,58	270,96	,000
ORMec*PSPSize	6962881,86	4	1740720,46	57,18	,000
DF*PSPSize	17418973,91	4	4354743,48	143,04	,000
ORMec*DF*PSPSize	9672982,61	8	1209122,83	39,72	,000
ORMec*DR	225420728,52	4	56355182,13	1851,11	,000
DF*DR	76235720,45	4	19058930,11	626,03	,000
ORMec*DF*DR	182076460,780	8	22759557,60	747,59	,000
PSPSize*DR	163649,080	4	40912,27	1,34	,252
ORMec*PSPSize*DR	170616,51	8	21327,06	,70	,691
DF * PSPSize * DR	85139,29	8	10642,41	,35	,946
ORMec * DF * PSPSize * DR	269099,41	16	16818,71	,55	,919
Error	22193633,80	729	30443,94		
Total	5121685517,66	810			
Corrected Total	1213108395,37	809			

a R Squared = ,982 (Adjusted R Squared = ,980)

Table 3.14. Pairwise Comparisons of OR Mechanisms in terms of MLT

(I) ORMec	(J) ORMec	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	287,955(*)	15,017	,000	258,473	317,437
	3,00	444,883(*)	15,017	,000	415,401	474,364
2,00	1,00	-287,955(*)	15,017	,000	-317,437	-258,473
	3,00	156,928(*)	15,017	,000	127,446	186,410
3,00	1,00	-444,883(*)	15,017	,000	-474,364	-415,401
	2,00	-156,928(*)	15,017	,000	-186,410	-127,446

* The mean difference is significant at the ,05 level.

Table 3.15. Pairwise Comparisons of DF

(I) DF	(J) DF	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	1581,290(*)	15,017	,000	1551,808	1610,772
	3,00	1484,678(*)	15,017	,000	1455,196	1514,159
2,00	1,00	-1581,290(*)	15,017	,000	-1610,772	-1551,808
	3,00	-96,612(*)	15,017	,000	-126,094	-67,131
3,00	1,00	-1484,678(*)	15,017	,000	-1514,159	-1455,196
	2,00	96,612(*)	15,017	,000	67,131	126,094

* The mean difference is significant at the ,05 level.

Table 3.16. Pairwise Comparisons of PSP Size

(I) PSPSize	(J) PSPSize	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	-123,026(*)	15,017	,000	-152,508	-93,545
	3,00	-300,175(*)	15,017	,000	-329,657	-270,693
2,00	1,00	123,026(*)	15,017	,000	93,545	152,508
	3,00	-177,149(*)	15,017	,000	-206,630	-147,667
3,00	1,00	300,175(*)	15,017	,000	270,693	329,657
	2,00	177,149(*)	15,017	,000	147,667	206,630

* The mean difference is significant at the ,05 level.

Table 3.17. Pairwise Comparisons of DR

(I) DR	(J) DR	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	460,744(*)	15,017	,000	431,262	490,225
	3,00	1133,232(*)	15,017	,000	1103,750	1162,714
2,00	1,00	-460,744(*)	15,017	,000	-490,225	-431,262
	3,00	672,489(*)	15,017	,000	643,007	701,970
3,00	1,00	-1133,232(*)	15,017	,000	-1162,714	-1103,750
	2,00	-672,489(*)	15,017	,000	-701,970	-643,007

* The mean difference is significant at the ,05 level.

3.7.2.3. The main and interaction effects of factors on SFTT

From Table 3.18, it is seen that all main factors and some factor interactions have significant effect on SFTT performance. PSPSize*DR, ORMec*PSPSize*DR, Flexibility*PSPSize*DR, ORMec*Flexibility*PSPSize*DR factor interactions have no significant effect on SFTT performance. In Tables 3.19-3.22 pairwise comparisons of main factors are given. From Table 3.19, it is seen that the mean difference of the levels of OR mechanisms is significant. Also, AGGWNQ OR mechanism performs the best SFTT performance. From Table 3.20, it is seen that the mean difference of the levels of the DF is significant. Also, the best SFTT performance is achieved at intermediate DF. From Table 3.21, it is seen that the mean difference of the low and the intermediate level of the PSP size is insignificant. Nevertheless, the mean difference of the high and the other levels of PSP size are significant. However, the best SFTT performance is achieved at low PSP size. From Table 3.22, it is seen that the mean difference of the levels of the DR is significant. Also, the best SFTT performance is achieved when SPT dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the SFTT performance of the shop.

Table 3.18. ANOVA results for SFTT

Source	Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1718935863,34[(a)]	80	21486698,29	1941,599	,000
Intercept	869342841,69	1	869342841,69	78556,290	,000
ORMec	798921566,34	2	399460783,17	36096,412	,000
DF	90737862,94	2	45368931,47	4099,666	,000
PSPSize	155333,558	2	77666,78	7,018	,001
DR	149542417,69	2	74771208,85	6756,539	,000
ORMec * DF	176487884,54	4	44121971,14	3986,987	,000
ORMec * PSPSize	299467,03	4	74866,76	6,765	,000
DF * PSPSize	311637,76	4	77909,44	7,040	,000
ORMec*DF*PSPSize	592287,63	8	74035,95	6,690	,000
ORMec * DR	246295199,43	4	61573799,86	5563,984	,000
DF * DR	84198708,86	4	21049677,21	1902,109	,000
ORMec * DF * DR	171324820,96	8	21415602,62	1935,175	,000
PSPSize * DR	8502,44	4	2125,61	,192	,943
ORMec*PSPSize*DR	19987,39	8	2498,42	,226	,986
DF * PSPSize * DR	10038,52	8	1254,82	,113	,999
ORMec * DF * PSPSize * DR	30148,25	16	1884,27	,170	1,000
Error	8067475,32	729	11066,50		
Total	2596346180,35	810			
Corrected Total	1727003338,66	809			

[a] R Squared = ,968 (Adjusted R Squared = ,964)

Table 3.19. Pairwise Comparisons of OR Mechanisms in terms of SFTT

(I) ORMec	(J) ORMec	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	2129,231[(*)]	9,054	,000	2111,456	2147,006
	3,00	2083,554[(*)]	9,054	,000	2065,779	2101,329
2,00	1,00	-2129,231[(*)]	9,054	,000	-2147,006	-2111,456
	3,00	-45,677[(*)]	9,054	,000	-63,452	-27,902
3,00	1,00	-2083,554[(*)]	9,054	,000	-2101,329	-2065,779
	2,00	45,677[(*)]	9,054	,000	27,902	63,452

* The mean difference is significant at the ,05 level.

Table 3.20. Pairwise Comparisons of DF in terms of SFTT

(I) DF	*(J) DF*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	723,092(*)	9,054	,000	705,317	740,866
	3,00	696,140(*)	9,054	,000	678,365	713,915
2,00	1,00	-723,092(*)	9,054	,000	-740,866	-705,317
	3,00	-26,952(*)	9,054	,003	-44,727	-9,177
3,00	1,00	-696,140(*)	9,054	,000	-713,915	-678,365
	2,00	26,952(*)	9,054	,003	9,177	44,727

* The mean difference is significant at the ,05 level.

Table 3.21. Pairwise Comparisons of PSP Size in terms of SFTT

(I) PSPSize	*(J) PSPSize*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	-15,934	9,054	,079	-33,709	1,841
	3,00	-33,900(*)	9,054	,000	-51,675	-16,126
2,00	1,00	15,934	9,054	,079	-1,841	33,709
	3,00	-17,966(*)	9,054	,048	-35,741	-,192
3,00	1,00	33,900(*)	9,054	,000	16,126	51,675
	2,00	17,966(*)	9,054	,048	,192	35,741

* The mean difference is significant at the ,05 level.

Table 3.22. Pairwise Comparisons of DR in terms of SFTT

(I) DR	*(J) DR*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	419,094(*)	9,054	,000	401,319	436,869
	3,00	1045,646(*)	9,054	,000	1027,871	1063,421
2,00	1,00	-419,094(*)	9,054	,000	-436,869	-401,319
	3,00	626,552(*)	9,054	,000	608,777	644,327
3,00	1,00	-1045,646(*)	9,054	,000	-1063,421	-1027,871
	2,00	-626,552(*)	9,054	,000	-644,327	-608,777

* The mean difference is significant at the ,05 level.

3.7.2.4. The main and interaction effects of factors on APWT

From Table 3.23, it is seen that all main factors and interactions other than PSP Size*DR, ORMec*PSP Size*DR, Flexibility*PSP Size*DR, ORMec*Flexibility*PSP Size*DR have significant effect on APWT performance. In Tables 3.24-3.27 pairwise comparisons of main factors are given. From Table 3.24 it is seen that the mean difference of the levels of OR mechanisms is significant. Also, certainly the best APWT performance is attained by IMR OR mechanism due to its operating mechanism. From Table 3.25 it is seen that the mean difference of the levels of the DF is significant. Also, the best APWT performance is achieved at intermediate DF. From Table 3.26 it is seen that the mean difference of the levels of the PSP Size is significant. Also, the best APWT performance is attained at low PSP Size. From Table 3.27, it is seen that the mean difference of the levels of the DR is significant. Also, the best APWT performance is achieved when SPT dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the APWT performance of the shop.

Table 3.23. ANOVA results for APWT

Source	Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	800902740,27[(a)]	80	10011284,25	480,43	,000
Intercept	1116392674,50	1	1116392674,50	53573,84	,000
ORMec	563946076,24	2	281973038,12	13531,42	,000
DF	124588148,98	2	62294074,49	2989,39	,000
PSPSize	10132295,12	2	5066147,56	243,12	,000
DR	1123704,67	2	561852,33	26,96	,000
ORMec*DF	65566693,20	4	16391673,30	786,61	,000
ORMec*PSPSize	7319720,67	4	1829930,17	87,82	,000
DF*PSPSize	13719914,88	4	3429978,72	164,60	,000
ORMec*DF*PSPSize	10169361,68	8	1271170,21	61,00	,000
ORMec*DR	1347967,29	4	336991,82	16,17	,000
DF*DR	694007,48	4	173501,87	8,33	,000
ORMec*DF*DR	1785931,45	8	223241,43	10,71	,000
PSPSize*DR	110240,00	4	27560,00	1,32	,260
ORMec*PSPSize*DR	136523,40	8	17065,43	,82	,586
DF*PSPSize*DR	55675,04	8	6959,38	,33	,953
ORMec*DF*PSPSize*DR	206480,17	16	12905,01	,62	,870
Error	15191186,85	729	20838,39		
Total	1932486601,62	810			
Corrected Total	816093927,12	809			

[a] R Squared = ,981 (Adjusted R Squared = ,979)

Table 3.24. Pairwise Comparisons of OR Mechanisms in terms of APWT

(I) ORMec	(J) ORMec	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	-1864,179[(*)]	12,424	,000	-1888,570	-1839,788
	3,00	-1657,804[(*)]	12,424	,000	-1682,195	-1633,413
2,00	1,00	1864,179[(*)]	12,424	,000	1839,788	1888,570
	3,00	206,375[(*)]	12,424	,000	181,984	230,766
3,00	1,00	1657,804[(*)]	12,424	,000	1633,413	1682,195
	2,00	-206,375[(*)]	12,424	,000	-230,766	-181,984

* The mean difference is significant at the ,05 level.

Table 3.25. Pairwise Comparisons of DF in terms of APWT

(I) DF	*(J) DF*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	865,731(*)	12,424	,000	841,340	890,122
	3,00	793,474(*)	12,424	,000	769,083	817,866
2,00	1,00	-865,731(*)	12,424	,000	-890,122	-841,340
	3,00	-72,257(*)	12,424	,000	-96,648	-47,866
3,00	1,00	-793,474(*)	12,424	,000	-817,866	-769,083
	2,00	72,257(*)	12,424	,000	47,866	96,648

* The mean difference is significant at the ,05 level.

Table 3.26. Pairwise Comparisons of PSP Size in terms of APWT

(I) PSPSize	*(J) PSPSize*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	-108,020(*)	12,424	,000	-132,412	-83,629
	3,00	-272,045(*)	12,424	,000	-296,436	-247,654
2,00	1,00	108,020(*)	12,424	,000	83,629	132,412
	3,00	-164,025(*)	12,424	,000	-188,416	-139,633
3,00	1,00	272,045(*)	12,424	,000	247,654	296,436
	2,00	164,025(*)	12,424	,000	139,633	188,416

* The mean difference is significant at the ,05 level.

Table 3.27. Pairwise Comparisons of DR in terms of APWT

(I) DR	*(J) DR*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	43,973(*)	12,424	,000	19,581	68,364
	3,00	91,215(*)	12,424	,000	66,824	115,606
2,00	1,00	-43,973(*)	12,424	,000	-68,364	-19,581
	3,00	47,242(*)	12,424	,000	22,851	71,634
3,00	1,00	-91,215(*)	12,424	,000	-115,606	-66,824
	2,00	-47,242(*)	12,424	,000	-71,634	-22,851

* The mean difference is significant at the ,05 level.

3.7.2.5. The main and interaction effects of factors on AT

From Table 3.28, it is seen that all main factors and factor interactions except ORMec*PSP Size*DR have significant effect on AT performance. In Tables 3.29-3.32 pairwise comparisons of main factors are given. From Table 3.29, it is seen that the mean difference of the levels of OR mechanisms is significant. Also, IMR OR mechanism performs the best AT performance. From Table 3.30 it is seen that the mean difference of the levels of DF is significant. Also, the best AT performance is attained at high DF. From Table 3.31, it is seen that the mean difference of the intermediate and high PSP size is insignificant. Nevertheless, the mean differences of low and higher PSP sizes are significant. However, the best AT performance is attained at high level of PSP size. From Table 3.32, it is seen that the mean difference of the low and the intermediate level of the DR is insignificant. Nevertheless, the mean differences of high and the other levels of DR are significant. However, the best AT performance is achieved when FIFO DR is used. Note that, due to interaction effects main factor effects should be considered together with interaction effects to optimize the AT performance of the shop.

Table 3.28. ANOVA results for AT

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	754592213,97[a]	80	9432402,68	384,96	,000
Intercept	1118969386,49	1	1118969386	45668,30	,000
ORMec	35937667,61	2	17968833,8	733,36	,000
DF	533707272,42	2	266853636	10891,05	,000
PSPSize	1219925,93	2	609962,97	24,89	,000
DR	42131877,44	2	21065938,7	859,76	,000
ORMec*DF	32412225,36	4	8103056,34	330,71	,000
ORMec*PSPSize	2186992,37	4	546748,09	22,31	,000
DF*PSPSize	4022676,33	4	1005669,08	41,04	,000
ORMec*DF*PSPSize	4222762,82	8	527845,35	21,54	,000
ORMec*DR	11719657,79	4	2929914,45	119,58	,000
DF*DR	12526178,43	4	3131544,61	127,81	,000
ORMec * DF * DR	71838642,98	8	8979830,37	366,49	,000
PSPSize * DR	481171,40	4	120292,85	4,91	,001
ORMec * PSPSize * DR	291191,08	8	36398,89	1,49	,159
DF * PSPSize * DR	872192,51	8	109024,06	4,45	,000
ORMec*DF*PSPSize*DR	1021779,50	16	63861,22	2,61	,001
Error	17862033,40	729	24502,10		
Total	1891423633,86	810			
Corrected Total	772454247,37	809			

a R Squared = ,977 (Adjusted R Squared = ,974)

Table 3.29. Pairwise Comparisons of OR Mechanisms in terms of AT

(I) ORMec	*(J) ORMec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference(a)*	
					Upper Bound	*Lower Bound*
1,00	2,00	-492,404(*)	13,472	,000	-518,853	-465,955
	3,00	-379,646(*)	13,472	,000	-406,095	-353,198
2,00	1,00	492,404(*)	13,472	,000	465,955	518,853
	3,00	112,758(*)	13,472	,000	86,309	139,206
3,00	1,00	379,646(*)	13,472	,000	353,198	406,095
	2,00	-112,758(*)	13,472	,000	-139,206	-86,309

* The mean difference is significant at the ,05 level.

Table 3.20. Pairwise Comparisons of DF in terms of AT

(I) DF	(J) DF	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	1672,723(*)	13,472	,000	1646,274	1699,172
	3,00	1767,242(*)	13,472	,000	1740,793	1793,691
2,00	1,00	-1672,723(*)	13,472	,000	-1699,172	-1646,274
	3,00	94,519(*)	13,472	,000	68,070	120,967
3,00	1,00	-1767,242(*)	13,472	,000	-1793,691	-1740,793
	2,00	-94,519(*)	13,472	,000	-120,967	-68,070

* The mean difference is significant at the ,05 level.

Table 3.31. Pairwise Comparisons of PSP Size in terms of AT

(I) PSP Size	(J) PSP Size	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	68,139(*)	13,472	,000	41,690	94,587
	3,00	91,473(*)	13,472	,000	65,024	117,922
2,00	1,00	-68,139(*)	13,472	,000	-94,587	-41,690
	3,00	23,334	13,472	,084	-3,114	49,783
3,00	1,00	-91,473(*)	13,472	,000	-117,922	-65,024
	2,00	-23,334	13,472	,084	-49,783	3,114

* The mean difference is significant at the ,05 level.

Table 3.32. Pairwise Comparisons of DR in terms of AT

(I) DR	(J) DR	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference(a)	
					Upper Bound	Lower Bound
1,00	2,00	-21,206	13,472	,116	-47,655	5,243
	3,00	-494,058(*)	13,472	,000	-520,507	-467,609
2,00	1,00	21,206	13,472	,116	-5,243	47,655
	3,00	-472,852(*)	13,472	,000	-499,301	-446,403
3,00	1,00	494,058(*)	13,472	,000	467,609	520,507
	2,00	472,852(*)	13,472	,000	446,403	499,301

* The mean difference is significant at the ,05 level.

3.7.2.6. The main and interaction effects of factors on AQWT

From Table 3.33, it is seen that all main factors and factor interactions except PSP Size*DR, OR Mec*PSP Size*DR, DF*PSP Size*DR, OR Mec*DF*PSP Size*DR have significant effect on AQWT performance. In Tables 3.34-3.35 pairwise comparisons of main factors are given. From Table 3.34, it is seen that the mean differences of the levels of OR mechanisms are significant. Also, AGGWNQ OR mechanism performs the best AQWT performance. From Table 3.35, it is seen that the mean differences of the levels of DF are significant. Also, the best AQWT performance is attained at intermediate DF. From Table 3.36, it is seen that the mean differences of the intermediate and other levels of PSP size are insignificant. Nevertheless, mean difference of low and high PSP size is significant. However, the best AQWT performance is attained at low PSP size is used. From Table 3.37, it is seen that the mean difference of the levels of the DR is significant. Also, the best AQWT performance is achieved when SPT dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the AQWT performance of the shop.

Table 3.33. ANOVA results for AQWT

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	78462383,63[a]	80	980779,80	2205,67	,000
Intercept	29436258,85	1	29436258,85	66199,12	,000
ORMec	33935802,76	2	16967901,38	38159,07	,000
DF	4462116,98	2	2231058,49	5017,42	,000
PSPSize	4175,60	2	2087,80	4,70	,009
DR	7057319,47	2	3528659,74	7935,59	,000
ORMec*DF	8765962,46	4	2191490,62	4928,44	,000
ORMec*PSPSize	11008,35	4	2752,09	6,19	,000
DF*PSPSize	8432,34	4	2108,08	4,74	,001
ORMec*DF*PSPSize	21817,91	8	2727,24	6,13	,000
ORMec*DR	12088836,71	4	3022209,18	6796,64	,000
DF*DR	3990400,86	4	997600,22	2243,50	,000
ORMec*DF*DR	8114018,94	8	1014252,37	2280,95	,000
PSPSize*DR	149,73	4	37,43	,08	,987
ORMec*PSPSize*DR	860,57	8	107,57	,24	,983
DF*PSPSize*DR	208,01	8	26,00	,06	1,00
ORMec*DF*PSPSize*DR	1272,94	16	79,56	,18	1,00
Error	324158,89	729	444,66		
Total	108222801,4	810			
Corrected Total	78786542,52	809			

[a] R Squared = ,996 (Adjusted R Squared = ,995)

Table 3.34. Pairwise Comparisons of OR Mechanisms in terms of AQWT

(I) OR Mec	*(J) OR Mec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	438,305(*)	1,815	,000	434,742	441,868
	3,00	429,981(*)	1,815	,000	426,418	433,544
2,00	1,00	-438,305(*)	1,815	,000	-441,868	-434,742
	3,00	-8,324(*)	1,815	,000	-11,887	-4,761
3,00	1,00	-429,981(*)	1,815	,000	-433,544	-426,418
	2,00	8,324(*)	1,815	,000	4,761	11,887

* The mean difference is significant at the ,05 level.

Table 3.35. Pairwise Comparisons of DF in terms of AQWT

(I) DF	*(J) DF*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	160,016(*)	1,815	,000	156,453	163,579
	3,00	154,745(*)	1,815	,000	151,182	158,308
2,00	1,00	-160,016(*)	1,815	,000	-163,579	-156,453
	3,00	-5,271(*)	1,815	,004	-8,834	-1,708
3,00	1,00	-154,745(*)	1,815	,000	-158,308	-151,182
	2,00	5,271(*)	1,815	,004	1,708	8,834

* The mean difference is significant at the ,05 level.

Table 3.36. Pairwise Comparisons of PSP Size in terms of AQWT

(I) PSP Size	*(J) PSP Size*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	-2,240	1,815	,218	-5,803	1,323
	3,00	-5,528(*)	1,815	,002	-9,091	-1,965
2,00	1,00	2,240	1,815	,218	-1,323	5,803
	3,00	-3,289	1,815	,070	-6,852	,274
3,00	1,00	5,528(*)	1,815	,002	1,965	9,091
	2,00	3,289	1,815	,070	-,274	6,852

* The mean difference is significant at the ,05 level.

Table 3.37. Pairwise Comparisons OF DR in terms of AQWT

(I) DR	*(J) DR*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	109,920(*)	1,815	,000	106,357	113,483
	3,00	228,585(*)	1,815	,000	225,022	232,148
2,00	1,00	-109,920(*)	1,815	,000	-113,483	-106,357
	3,00	118,665(*)	1,815	,000	115,102	122,228
3,00	1,00	-228,585(*)	1,815	,000	-232,148	-225,022
	2,00	-118,665(*)	1,815	,000	-122,228	-115,102

* The mean difference is significant at the ,05 level.

3.7.2.7. The main and interaction effects of factors on T (%)

From Table 3.38, it is seen that all main factors and interactions except OR Mec*PSP Size*DR, OR Mec*Flexibility*PSP Size*DR have significant effect on T (%) performance. In Tables 3.39-3.40, pairwise comparisons of main factors are given. From Table 3.39, it is seen that the mean difference of the levels of OR mechanisms is significant. Also, AGGWNQ OR mechanism performs the best T (%) performance. From Table 3.40, it is seen that the mean difference of the levels of the DF is significant. Also, the best T (%) performance is attained at intermediate DF. From Table 3.41, it is seen that the mean difference of the levels of the PSP size is significant. Also, the best T (%) performance is achieved when the PSP size is set to its low level. From Table 3.42, it is seen that the mean difference of the levels of the DR is significant. Also, the best T (%) performance is achieved when EDD dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the T (%) performance of the shop.

Table 3.38. ANOVA results for T (%)

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	379017,61[(a)]	80	4737,720	472,47	,000
Intercept	2168868,39	1	2168868,39	216293,44	,000
ORMec	3919,26	2	1959,63	195,43	,000
DF	3216,96	2	1608,48	160,41	,000
PSPSize	1026,05	2	513,03	51,16	,000
DR	175684,18	2	87842,09	8760,18	,000
ORMec*DF	8869,72	4	2217,43	221,14	,000
ORMec*PSPSize	734,67	4	183,67	18,32	,000
DF*PSPSize	1308,42	4	327,11	32,62	,000
ORMec*DF*PSPSize	951,19	8	118,90	11,86	,000
ORMec*DR	26950,70	4	6737,68	671,92	,000
DF*DR	93461,67	4	23365,42	2330,15	,000
ORMec*DF*DR	62130,31	8	7766,29	774,50	,000
PSPSize*DR	168,38	4	42,09	4,20	,002
ORMec*PSPSize*DR	95,30	8	11,91	1,19	,303
DF*PSPSize*DR	309,48	8	38,69	3,86	,000
ORMec*DF*PSPSize*DR	191,31	16	11,96	1,19	,268
Error	7310,00	729	10,03		
Total	2555196,00	810			
Corrected Total	386327,61	809			

[a] R Squared = ,981 (Adjusted R Squared = ,979)

Table 3.39. Pairwise Comparisons of OR Mechanisms in terms of T (%)

(I) OR Mec	*(J) OR Mec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	5,093(*)	,273	,000	4,558	5,628
	3,00	4,070(*)	,273	,000	3,535	4,605
2,00	1,00	-5,093(*)	,273	,000	-5,628	-4,558
	3,00	-1,022(*)	,273	,000	-1,557	-,487
3,00	1,00	-4,070(*)	,273	,000	-4,605	-3,535
	2,00	1,022(*)	,273	,000	,487	1,557

* The mean difference is significant at the ,05 level.

Table 3.40. Pairwise Comparisons of DF in terms of T (%)

(I) DF	(J) DF	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	4,652(*)	,273	,000	4,117	5,187
	3,00	1,044(*)	,273	,000	,509	1,579
2,00	1,00	-4,652(*)	,273	,000	-5,187	-4,117
	3,00	-3,607(*)	,273	,000	-4,142	-3,072
3,00	1,00	-1,044(*)	,273	,000	-1,579	-,509
	2,00	3,607(*)	,273	,000	3,072	4,142

* The mean difference is significant at the ,05 level.

Table 3.41. Pairwise Comparisons of PSP Size in terms of T (%)

(I) PSPSize	(J) PSPSize	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	-,622(*)	,273	,023	-1,157	-,087
	3,00	-2,637(*)	,273	,000	-3,172	-2,102
2,00	1,00	,622(*)	,273	,023	,087	1,157
	3,00	-2,015(*)	,273	,000	-2,550	-1,480
3,00	1,00	2,637(*)	,273	,000	2,102	3,172
	2,00	2,015(*)	,273	,000	1,480	2,550

* The mean difference is significant at the ,05 level.

Table 3.42. Pairwise Comparisons of DR in term of T(%)

(I) DR	(J) DR	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	36,070(*)	,273	,000	35,535	36,605
	3,00	18,504(*)	,273	,000	17,969	19,039
2,00	1,00	-36,070(*)	,273	,000	-36,605	-35,535
	3,00	-17,567(*)	,273	,000	-18,102	-17,032
3,00	1,00	-18,504(*)	,273	,000	-19,039	-17,969
	2,00	17,567(*)	,273	,000	17,032	18,102

* The mean difference is significant at the ,05 level

3.7.2.8. The main and interaction effects of factors on M

From Table 3.43, it is seen that all main factors and factor interactions other except PSP Size*DR, OR Mec*PSP Size*DR, Flexibility*PSP Size*DR, OR Mec*Flexibility*PSP Size*DR have significant effect on M performance. In Tables 3.44-3.47 pairwise comparisons of main factors are given. From Table 3.44, it is seen that the mean difference of the levels of OR mechanisms is significant. Also, WCWT OR mechanism performs the best M performance. From Table 3.45, it is seen that the mean difference of the intermediate and the high level of DF is insignificant. Nevertheless, the mean differences of the low and higher levels of DF are significant. However, the best M performance is achieved when the high level of DF is used. From Table 3.46, it is seen that the mean differences of the levels of the PSP size are significant. Also, the best M performance is attained at high level of PSP size. From Table 3.47, it is seen that the mean differences of the levels of the DR are significant. Also, the best M performance is achieved when EDD dispatching rule is used. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the M performance of the shop.

Table 3.43. ANOVA results for M

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	25304057759,45[a]	80	316300721,99	3839,48	,000
Intercept	1850446169876,0	1	1850446169876,0	22462020,2	,000
ORMec	395369043,67	2	197684521,84	2399,63	,000
DF	22230348280,49	2	11115174140,24	134923,82	,000
PSPSize	220722697,33	2	110361348,66	1339,64	,000
DR	81527619,81	2	40763809,90	494,82	,000
ORMec*DF	1321842673,53	4	330460668,38	4011,36	,000
ORMec*PSPSize	114650384,36	4	28662596,09	347,93	,000
DF*PSPSize	430625596,09	4	107656399,02	1306,81	,000
ORMec*DF*PSPSize	224160180,23	8	28020022,53	340,13	,000
ORMec*DR	198547646,57	4	49636911,64	602,53	,000
DF*DR	34069969,32	4	8517492,33	103,39	,000
ORMec*DF*DR	50261395,16	8	6282674,40	76,26	,000
PSPSize*DR	58892,62	4	14723,15	,18	,949
ORMec*PSPSize*DR	513654,59	8	64206,82	,78	,621
DF*PSPSize*DR	198510,027	8	24813,75	,30	,966
ORMec*DF*PSPSize*DR	1161215,68	16	72575,98	,88	,592
Error	60055829,75	729	82381,11		
Total	1875810283465,2	810			
Corrected Total	25364113589,21	809			

[a] R Squared = ,998 (Adjusted R Squared = ,997)

Table 3.44. Pairwise Comparisons of OR mechanisms in terms of M

(I) ORMec	*(J) ORMec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	-1549,115(*)	24,703	,000	-1597,613	-1500,618
	3,00	-1404,380(*)	24,703	,000	-1452,877	-1355,883
2,00	1,00	1549,115(*)	24,703	,000	1500,618	1597,613
	3,00	144,736(*)	24,703	,000	96,238	193,233
3,00	1,00	1404,380(*)	24,703	,000	1355,883	1452,877
	2,00	-144,736(*)	24,703	,000	-193,233	-96,238

* The mean difference is significant at the ,05 level.

Table 3.45. Pairwise Comparisons of DF in terms of M

(I) DF	(J) DF	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	11103,878(*)	24,703	,000	11055,381	11152,375
	3,00	11122,384(*)	24,703	,000	11073,886	11170,881
2,00	1,00	-11103,878(*)	24,703	,000	-11152,375	-11055,381
	3,00	18,506	24,703	,454	-29,992	67,003
3,00	1,00	-11122,384(*)	24,703	,000	-11170,881	-11073,886
	2,00	-18,506	24,703	,454	-67,003	29,992

* The mean difference is significant at the ,05 level.

Table 3.46. Pairwise Comparisons of PSP Size in terms of M

(I) PSPSize	(J) PSPSize	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	956,474(*)	24,703	,000	907,977	1004,971
	3,00	1213,156(*)	24,703	,000	1164,658	1261,653
2,00	1,00	-956,474(*)	24,703	,000	-1004,971	-907,977
	3,00	256,682(*)	24,703	,000	208,185	305,179
3,00	1,00	-1213,156(*)	24,703	,000	-1261,653	-1164,658
	2,00	-256,682(*)	24,703	,000	-305,179	-208,185

* The mean difference is significant at the ,05 level.

Table 3.47. Pairwise Comparisons of DR in terms of M

(I) DR	(J) DR	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval for Difference	
					Upper Bound	Lower Bound
1,00	2,00	748,289(*)	24,703	,000	699,792	796,786
	3,00	555,745(*)	24,703	,000	507,248	604,242
2,00	1,00	-748,289(*)	24,703	,000	-796,786	-699,792
	3,00	-192,544(*)	24,703	,000	-241,041	-144,047
3,00	1,00	-555,745(*)	24,703	,000	-604,242	-507,248
	2,00	192,544(*)	24,703	,000	144,047	241,041

* The mean difference is significant at the ,05 level.

3.7.2.9. The main and interaction effects of factors on R

From Table 3.48, it is seen that all main factors and factor interactions except Flexibility*PSPSize*DR, ORMec*Flexibility*PSPSize*DR have significant effect on R performance. In Tables 3.49-3.52 pairwise comparisons of main factors are given. From Table 3.49 it is seen that the mean differences of the levels of OR mechanisms are significant. Also, IMR OR mechanism performs the best R performance. From Table 3.50, it is seen that the mean differences of the levels of DF is significant. Also, the best R performance is attained at high DF. From Table 3.51, it is seen that the mean differences of the levels of the PSP size are significant. Also, the best R performance is attained at high level of PSP size. From Table 3.52, it is seen that the mean differences of the levels of the DR are insignificant. This means, no matter whatever DR is used in terms of R performance. Note that, due to interaction effects, main factor effects should be considered together with interaction effects to optimize the M performance of the shop.

Table 3.48. ANOVA results for R

Source	*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Corrected Model	6462604265,31[(a)]	80	80782553,32	4064,87	,000
Intercept	1899413801,39	1	1899413801,4	95576,02	,000
ORMec	947683304,03	2	473841652,02	23843,09	,000
DF	3185528192,61	2	1592764096,3	80145,80	,000
PSPSize	251034723,66	2	125517361,83	6315,87	,000
DR	6204,68	2	3102,34	,16	,855
ORMec*DF	1588906543,49	4	397226635,87	19987,92	,000
ORMec*PSPSize	125869784,28	4	31467446,07	1583,40	,000
DF*PSPSize	238456237,41	4	59614059,35	2999,70	,000
ORMec*DF*PSPSize	122304436,56	8	15288054,57	769,28	,000
ORMec*DR	567422,95	4	141855,74	7,14	,000
DF*DR	259969,41	4	64992,35	3,27	,011
ORMec*DF*DR	525753,87	8	65719,23	3,31	,001
PSPSize*DR	211216,78	4	52804,20	2,66	,032
ORMec*PSPSize*DR	652077,05	8	81509,63	4,10	,000
DF*PSPSize*DR	157009,61	8	19626,20	,99	,444
ORMec*DF*PSPSize*DR	441388,91	16	27586,81	1,39	,140
Error	14487658,30	729	19873,33		
Total	8376505725,00	810			
Corrected Total	6477091923,61	809			

[a] R Squared = ,998 (Adjusted R Squared = ,998)

Table 3.49. Pairwise Comparisons of OR Mechanisms in terms of R

(I) ORMec	*(J) ORMec*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	-2307,867(*)	12,133	,000	-2331,686	-2284,047
	3,00	-2280,974(*)	12,133	,000	-2304,794	-2257,154
2,00	1,00	2307,867(*)	12,133	,000	2284,047	2331,686
	3,00	26,893(*)	12,133	,027	3,073	50,712
3,00	1,00	2280,974(*)	12,133	,000	2257,154	2304,794
	2,00	-26,893(*)	12,133	,027	-50,712	-3,073

* The mean difference is significant at the ,05 level

Table 3.50. Pairwise Comparisons of DF

(I) DF	*(J) DF*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	4199,730(*)	12,133	,000	4175,910	4223,549
	3,00	4213,885(*)	12,133	,000	4190,065	4237,705
2,00	1,00	-4199,730(*)	12,133	,000	-4223,549	-4175,910
	3,00	14,156	12,133	,244	-9,664	37,975
3,00	1,00	-4213,885(*)	12,133	,000	-4237,705	-4190,065
	2,00	-14,156	12,133	,244	-37,975	9,664

* The mean difference is significant at the ,05 level.

Table 3.51. Pairwise Comparisons of PSP Size

(I) PSP Size	*(J) PSP Size*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	965,133(*)	12,133	,000	941,314	988,953
	3,00	1316,848(*)	12,133	,000	1293,028	1340,668
2,00	1,00	-965,133(*)	12,133	,000	-988,953	-941,314
	3,00	351,715(*)	12,133	,000	327,895	375,535
3,00	1,00	-1316,848(*)	12,133	,000	-1340,668	-1293,028
	2,00	-351,715(*)	12,133	,000	-375,535	-327,895

* The mean difference is significant at the ,05 level.

Table 3.52. Pairwise Comparisons of DR

(I) DR	*(J) DR*	*Mean Difference (I-J)*	*Std. Error*	*Sig.*	*95% Confidence Interval for Difference*	
					Upper Bound	*Lower Bound*
1,00	2,00	-1,659	12,133	,891	-25,479	22,161
	3,00	4,863	12,133	,689	-18,957	28,683
2,00	1,00	1,659	12,133	,891	-22,161	25,479
	3,00	6,522	12,133	,591	-17,298	30,342
3,00	1,00	-4,863	12,133	,689	-28,683	18,957
	2,00	-6,522	12,133	,591	-30,342	17,298

* The mean difference is significant at the ,05 level.

3.7.2.10. Interaction Effect of OR mechanisms and DF

Up to here, main factor and interaction effects of all factors and the mean differences between the levels of main factors are analyzed. Now, the interaction effect of OR mechanism and DF on MAPE, MLT, SFTT, AT, AQWT, T (%), M, and R performances will be analyzed. To assist in analyzing the interaction effect of OR mechanism and DF, it is helpful to construct a graph of the average responses at each level of factor combination. Note that, only interaction effect of two factors will be analyzed. Thus, other factors' effects will be averaged for each level of DF and OR mechanism.

Also, MAPE, MLT, SFTT, AT, AQWT, T (%), M, and R performances of the shop is illustrated in appendix B for all other factor level combinations with respect to each PSP size, separately. Below, interaction effect of DF and OR Mechanism on MAPE, MLT, SFTT, AT, AQWT, T (%), M, and R performances illustrated and discussed, respectively.

3.7.2.10.1. Interaction effect of OR mechanisms and DF on MAPE

In Figure 3.1, interaction effect of DF and OR Mechanisms on MAPE performance is shown. The significant interaction is indicated by the lack of parallelism of the lines. Note that, these MAPE values are overall averages of all levels of DR and PSP size for each level of DF and OR mechanisms considered. Changing from low to intermediate DF, MAPE values with both AGGWNQ and WCWT OR mechanisms slightly increases, whereas it decreases significantly for IMR OR mechanism. Nevertheless, from intermediate to high DF, MAPE values with both AGGWNQ and WCWT OR mechanisms moderately decreases, whereas it increases for IMR OR mechanism.

Consequently, the level of DF significantly affects the MAPE performances of all OR mechanisms. For the low level of DF the MAPE performances of IMR and the others differs significantly. For intermediate level of DF the magnitude of the difference decreases, whereas high level of DF the magnitude of the difference moderately increases. AGGWNQ OR mechanism seems to give the best results if we want less loss of due date reliability as the DF increases. In appendix B, the overall MAPE performance of the shop is shown in Figures B.1-B.3 for each PSP size with respect to all other factor combinations, separately.

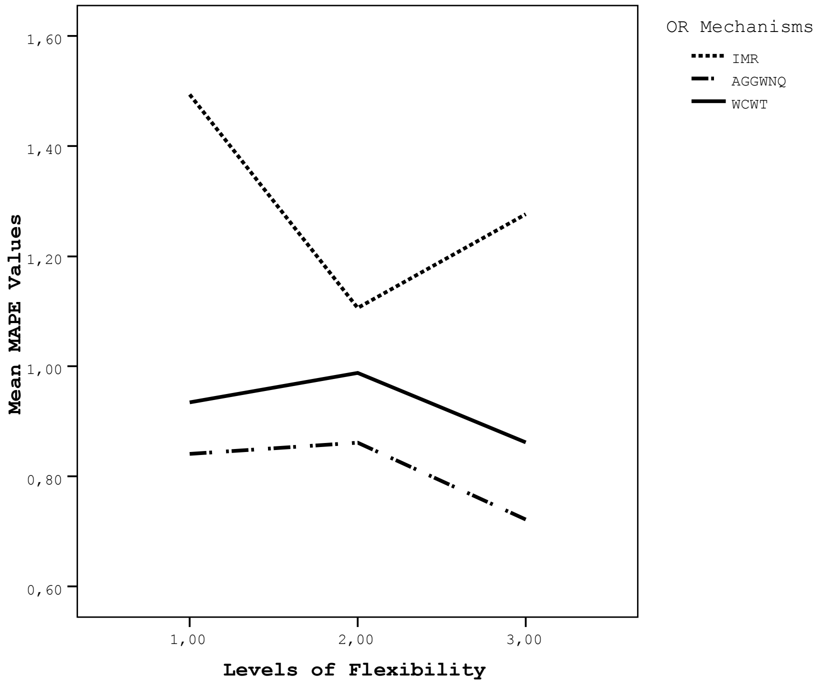


Figure 3.1. Interaction Effect of DF and OR Mechanism on MAPE

3.7.2.10.2. Interaction effect of OR mechanisms and DF on MLT

In Figure 3.2, interaction effect of DF and the OR Mechanisms on MLT performance is shown. In general, shorter MLT is attained at intermediate DF regardless of OR mechanism, whereas higher MLT is attained at low DF. Changing from low to intermediate DF, MLT with all OR mechanisms actually decreases. Note that, at low DF, MLT value with each OR mechanism significantly differs, whereas the magnitude of the difference decreases at higher DF. WCWT OR mechanism seems to give the best results if shorter MLT is desired regardless of DF. Also, intermediate level of flexibility provides the best MLT performance for each OR mechanism. In appendix B, The overall

MLT performance of the shop is shown in Figures B.4-B.6 for each PSP size with respect to all other factor combinations, separately.

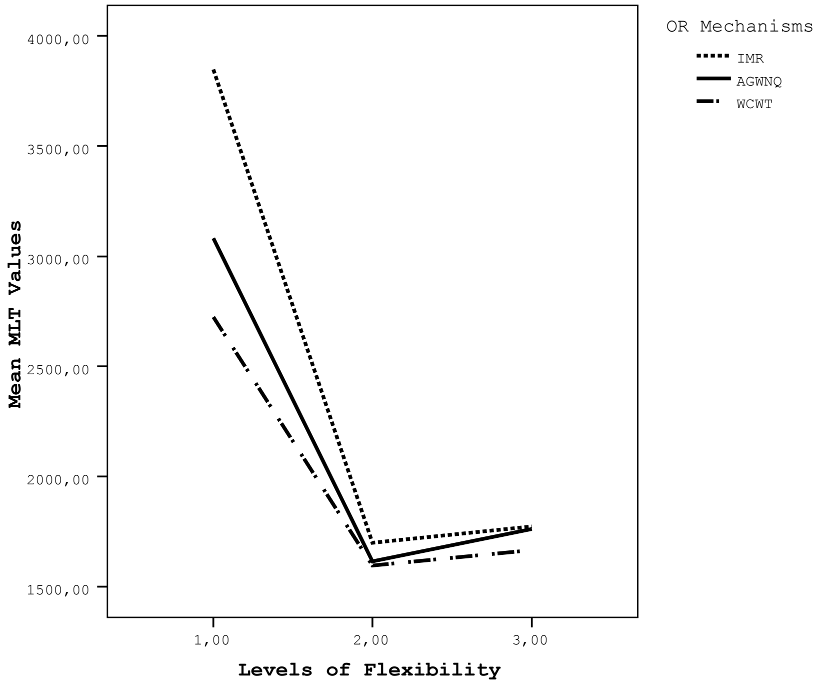


Figure 3.2. Interaction Effect of DF and OR Mechanism on MLT

3.7.2.10.3. Interaction effect of OR mechanisms and DF on SFTT

From Figure 3.3, as indicated by the parallelism of the lines, there is no interaction effect between DF and AGGWNQ and WCWT OR mechanisms. But, there is significant interaction between IMR OR mechanism and DF. At low DF longer SFTT is attained with IMR OR mechanism. Changing from low to intermediate DF, SFTT with IMR OR mechanism actually decreases. However, changing from intermediate to low degree of flexibility, SFTT with IMR OR mechanism slightly increases. AGGWNQ OR mechanism gives the best results regardless of DF if shorter SFTT is desired. In appendix B, the overall SFTT performance of the shop is shown in Figures B.7-B.9 for each PSP size with respect to all other factor combinations, separately.

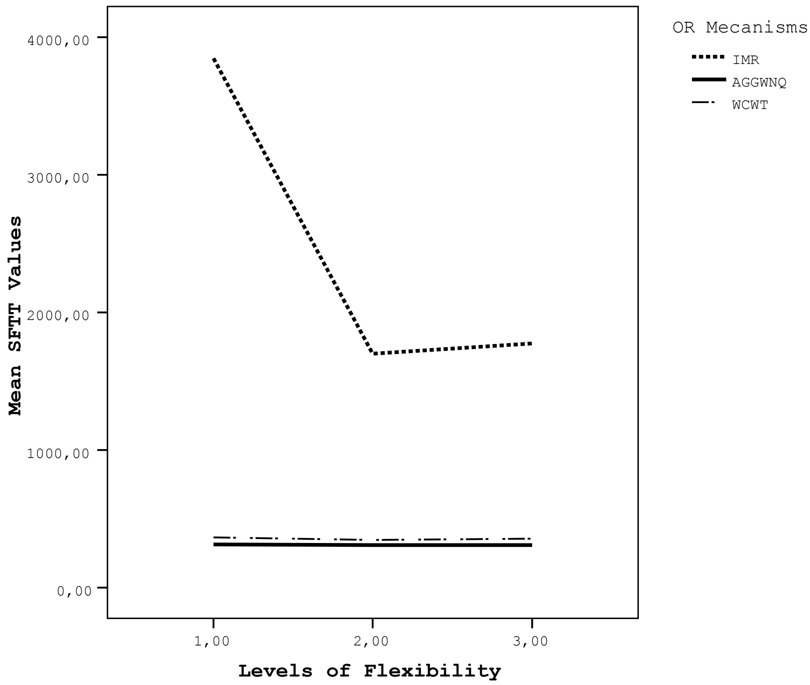


Figure 3.3. Interaction Effect of DF and OR Mechanism on SFTT

3.7.2.10.4. Interaction effect of OR mechanisms and DF on APWT

From Figure 3.4, as indicated by the parallelism of the line, there is no interaction between DF and IMR OR mechanism. This is not a surprising result, because according to the rationale behind the IMR OR mechanism orders do not need to wait in PSP. But, there is significant interaction between AGGWNQ and WCWT OR mechanisms and DF. Longer APWT is attained at low degree of flexibility for both OR mechanisms. Changing from low to intermediate DF, APWT with both OR mechanisms decreases. Note that, in this case the difference between these two OR mechanisms also decrease. Changing from intermediate to high DF, APWT with both OR mechanisms slightly increases. Note that, in this case the APWT with AGGWNQ increases more than the APWT with WCEDD. IMR OR mechanism seems to give the best results if minimum APWT performance is desired regardless of the DF. In appendix B, the overall APWT performance of the shop is shown in Figures B.10-B.12 for each PSP size with respect to all other factor combinations, separately.

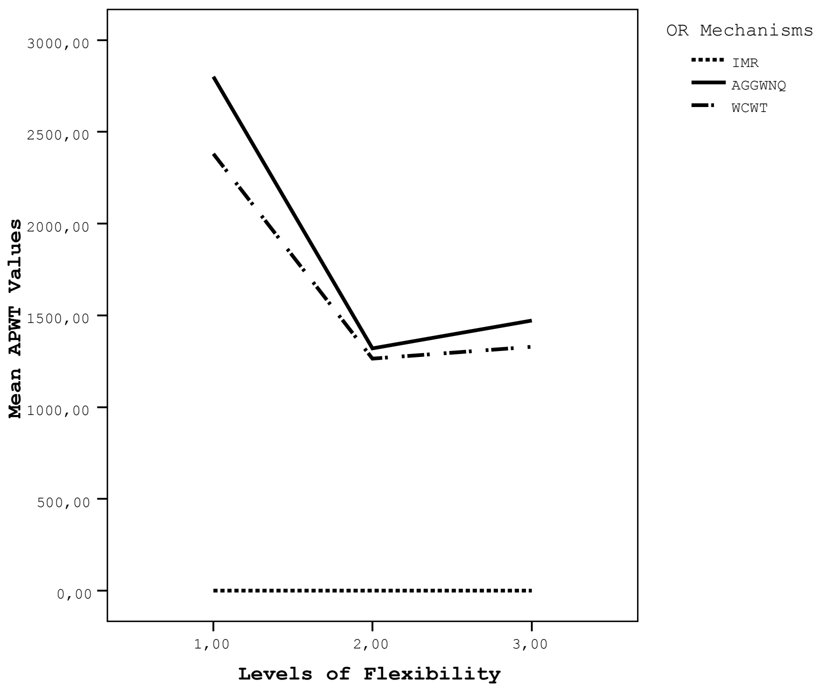


Figure 3.4. Interaction Effect of DF and OR Mechanism on APWT

3.7.2.10.5. Interaction effect of OR mechanisms and DF on AT

In Figure 3.5, interaction effect of DF and the OR Mechanisms on mean AT values is shown. In general, longer AT is attained at low DF, regardless of OR mechanism. Changing from low to intermediate DF, AT values with all OR mechanisms actually decreases. From intermediate to high DF, mean AT value with both AGGWNQ and WCWT OR mechanisms slightly decreases, whereas it slightly increases for IMR OR mechanism. Note that, for higher DF, the AT performance of AGGWNQ and WCWT is essentially the same. IMR OR mechanism seems to give the best results if minimum AT performance is desired regardless of DF. In appendix B, the overall AT performance of the shop is shown in Figures B.13-B.15 for each PSP size with respect to all other factor combinations, separately.

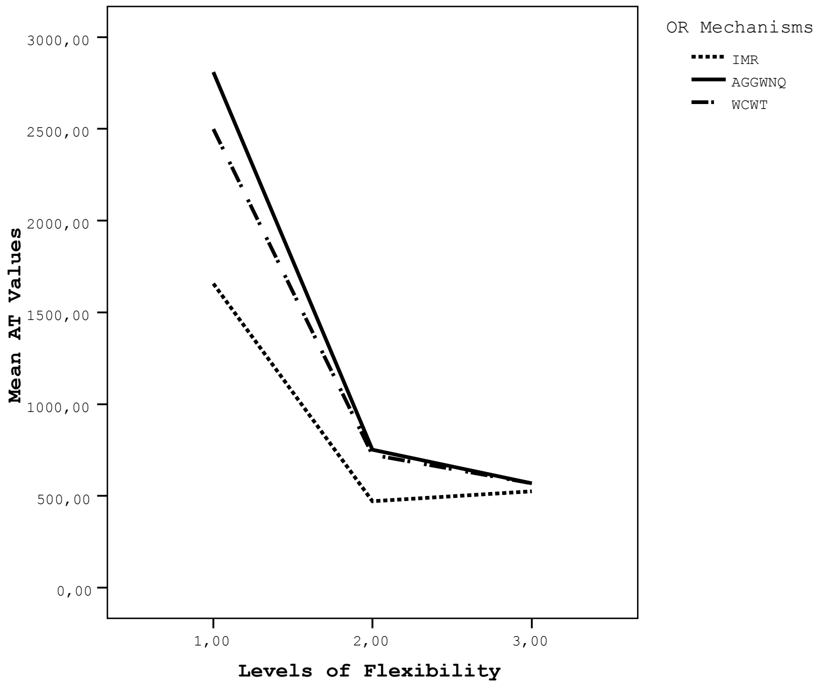


Figure 3.5. Interaction Effect of DF and OR Mechanism on AT

3.7.2.10.6. Interaction effect of OR mechanisms and DF on AQWT

From Figure 3.6, as indicated by the parallelism of the line, there is no interaction between DF and both AGGWNQ and WCWT OR mechanisms. This is mainly due to rationale behind each OR mechanism which stabilizes workload of the shop both as a whole and for each work center, respectively. In this respect, constant AQWTs are attained regardless of other factor levels. But, there is significant interaction between IMR OR mechanism and DF. Longer AQWT is attained at low DF for IMR OR mechanism. Changing from low to intermediate DF, AQWT with IMR OR mechanism actually decreases. From intermediate to high DF, AQWT with IMR OR mechanism slightly increases. AGGWNQ OR mechanism seems to give the best results if minimum AQWT is desired regardless of the degree of flexibility. In appendix B, The overall AQWT performance of the shop is shown in Figures B.16-B.18 for each PSP size with respect to all other factor combinations, separately.

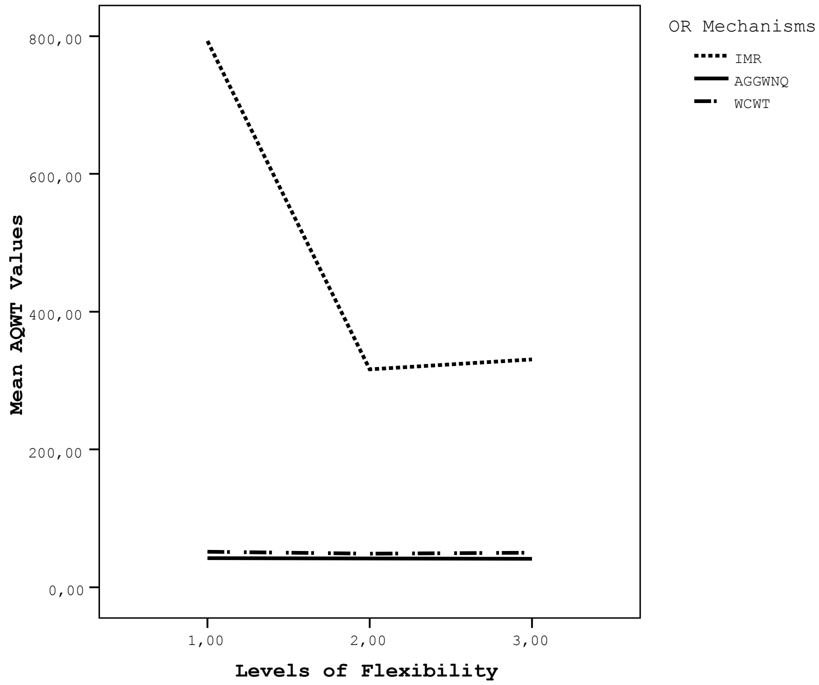


Figure 3.6. Interaction Effect of DF and OR Mechanism on AQWT

3.7.2.10.7. Interaction effect of OR mechanisms and DF on T (%)

In Figure 3.7, interaction effect of DF and the OR Mechanisms on mean T (%) values is shown. Much more orders become tardy with IMR OR mechanism at low DF. Note that, nearly half of the total finished orders with AGGWNQ and WCWT OR mechanisms become tardy at low DF. Changing from low to intermediate DF, percent of tardy orders with both AGGWNQ and IMR OR mechanisms actually decreases, whereas it increases for WCWT OR mechanism. From intermediate to high DF, percent of tardy orders with all OR mechanisms actually increases. Note that, T (%) performance of the shop is very sensitive to interaction between OR mechanisms and DF. However, AGGWNQ OR mechanism seems to give the best results if minimum T(%) values are desired at either low or intermediate DF. For high DF, IMR OR mechanism gives the best results. In appendix B, the overall T(%) performance of the shop is shown in Figures B.19-B.21 for each PSP size with respect to all other factor combinations, separately.

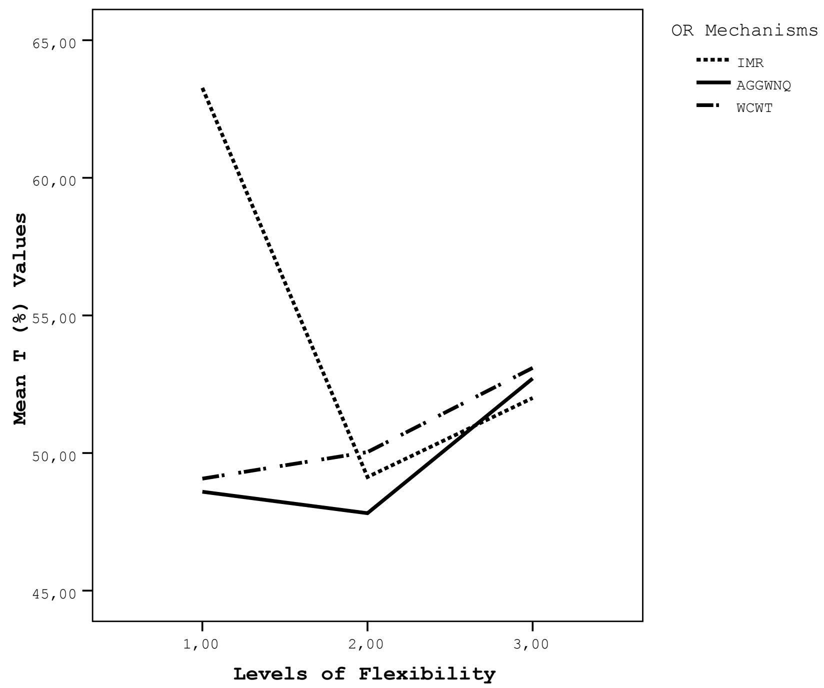


Figure 3.7. Interaction Effect of DF and OR Mechanism on T (%)

3.7.2.10.8. Interaction effect of OR mechanisms and DF on M

In Figure 3.8, interaction effect of the DF and the OR Mechanisms on mean M values is shown. Total completion time of 18000 orders is much longer with both AGGWNQ and WCWT OR mechanism at low degree of flexibility. Changing from low to intermediate DF, Total completion time of 18000 orders with all OR mechanisms actually decreases. In this case, total completion time of 18000 orders with both AGGWNQ and WCWT OR mechanisms is less than even that of IMR OR mechanism. From intermediate to high DF, Total completion time of 18000 orders slightly decreases for WCWT OR mechanism and essentially unchanged for both AGGWNQ and IMR OR mechanism. Consequently, IMR OR mechanism seems to give the best results if minimum M values are desired when the DF is low. However, WCWT OR mechanism gives the best results if minimum total completion time of 18000 orders is desired when the DF is either intermediate or high. Note that, AGGWNQ and WCWT OR mechanisms can be used interchangeably at intermediate DF is intermediate.

In appendix, B the overall M performance of the shop is shown in Figures B.22-B.24 for each PSP size with respect to all other factor combinations, separately.

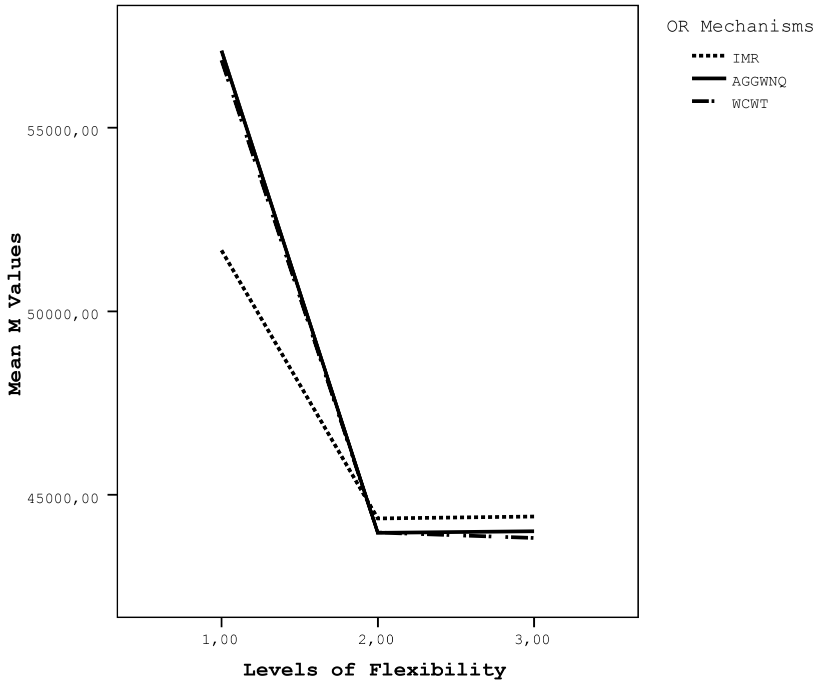


Figure 3.8. Interaction Effect of Flexibility and OR Mechanism on M

3.7.2.10.9. Interaction effect of OR mechanisms and DF on R

From Figure 3.9, as indicated by the parallelism of the line, there is no interaction effect between DF and IMR OR mechanism. This is a result of the rationale behind the IMR OR mechanism that all orders are released to the shop immediately regardless of the either shop or PSP based information which results in no rejection of any order. But, there is significant interaction between AQQWNQ and WCWT OR mechanisms and DF. Much more orders are rejected at low DF for both OR mechanisms. Changing from low to intermediate DF, mean number of total rejected orders with both OR mechanisms significantly decreases. Changing from intermediate to high DF, mean total number of total rejected orders with both OR mechanisms is essentially unchanged. IMR OR mechanism seems to give the best results if no rejection of any orders is desired regardless of the degree of flexibility. In appendix B, the overall R performance of the shop is shown in Figures B.25-B.27 for each PSP size with respect to all other factor combinations, separately.

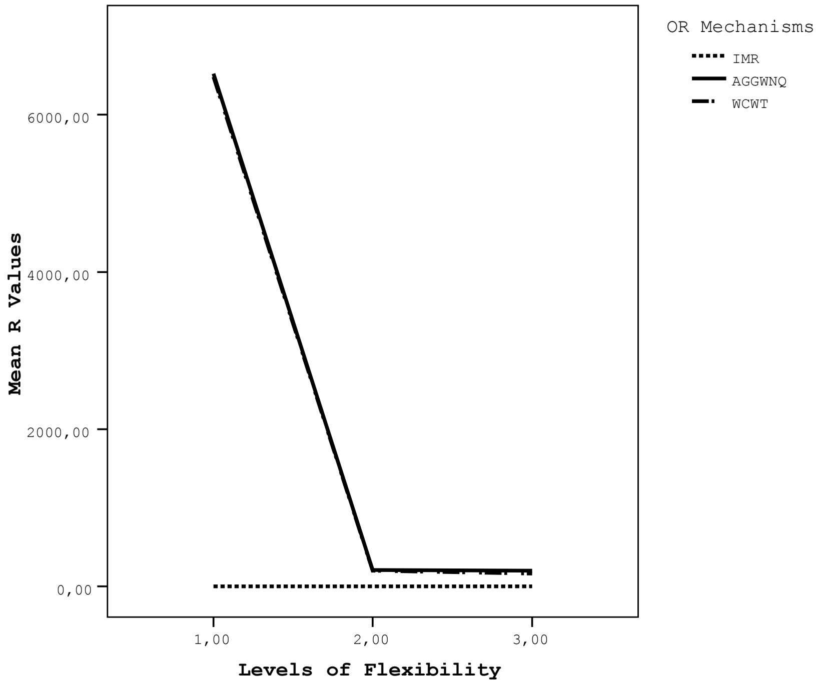


Figure 3.9. Interaction Effect of Flexibility and OR Mechanism on R

3.7.2.11. Average WIP levels with all OR Mechanisms at each DF

The WIP levels for each work center with all OR mechanism are given in Tables 3.53-3.55 in increasing order of DF, respectively. From Table 3.53, it is noticeable that a huge amount of average WIP with WC 1, WC 3, and WC 7 is occurred with IMR OR mechanism. Note that, in most manufacturing environment such amount of WIP is impractical due to space limitations. DR has significant effect on the average WIP with IMR OR mechanism whereas PSP size has no significant effect on the average WIP with IMR OR mechanism.

Average WIP with AGGWNQ at low PSP size is acceptable (i.e., due to space limitations) and remains nearly unchanged for each DR at each PSP size. Changing from low to intermediate PSP size, average WIP with AGGWNQ slightly increases for WC 1 and WC 7 whereas decreases for WC 3. In this case, average WIP with AGGWNQ is again in acceptable limits (i.e., due to space limitations) and remains nearly unchanged for each DR. From intermediate to high PSP size, average WIP with AGGWNQ slightly decreases for WC 1 and WC 7 whereas it increases for WC 3. Average WIP with AGGWNQ is in acceptable limits and only significantly affected by PSP size.

Average WIP with WCWT OR mechanism at low PSP is acceptable (i.e., due to space limitations) and remains nearly unchanged for each DR at each PSP size. Changing from low to intermediate PSP size, average WIP with WCWT slightly increases for WC 1 and WC 7 whereas it significantly increases for WC 3. From intermediate to high PSP size, average WIP with WCWT significantly increases for WC 3 and is essentially unchanged for WC 1 and WC 3.

Note that, well balanced average WIP across the WCs is attained at low PSP size with WCWT OR mechanism. But for higher levels of PSP size average WIP across the work centers with AGGWNQ is more balanced. Consequently, AGGWNQ OR mechanism gives the best results if less and more balanced average WIP is desired as the PSP size changes.

Table 3.53. Average WIP levels with all OR mechanisms at Low DF

OR Mec.	DF	PSP Size	DR	Work Centers 1	2	3	4	5	6	7	8	9	10	Var of WIP
IMR				923	1	1860	2	0	8	927	7	1	2	419882
AGGF			FIFO	13	0	57	1	0	1	12	1	0	1	314
WCEDD				8	0	27	1	0	2	8	2	0	1	69
IMR				723	1	1446	2	0	8	717	7	1	2	253643
AGGF		1000	EDD	13	0	55	1	0	1	15	1	0	1	296
WCEDD				7	0	24	1	0	2	8	2	0	1	55
IMR				758	1	1372	2	0	10	696	11	1	2	236403
AGGF			SPT	13	0	58	1	0	1	13	1	0	1	325
WCEDD				7	0	21	1	0	1	7	1	0	1	43
IMR				923	1	1860	2	0	8	927	7	1	2	419882
AGGF			FIFO	21	0	42	1	0	2	21	2	0	1	205
WCEDD				12	1	70	1	0	3	13	3	1	1	459
IMR				723	1	1446	2	0	8	717	7	1	2	253643
AGGF	0	2000	EDD	20	0	43	1	0	2	21	2	0	1	210
WCEDD				12	1	74	1	0	2	12	2	1	1	516
IMR				758	1	1372	2	0	10	696	11	1	2	236403
AGGF			SPT	20	0	46	1	0	1	20	1	0	1	234
WCEDD				12	0	56	1	0	2	12	2	0	1	299
IMR				923	1	1860	2	0	8	927	7	1	2	419882
AGGF			FIFO	16	0	50	1	0	2	16	2	1	1	247
WCEDD				13	1	149	1	0	3	13	3	1	1	2126
IMR				723	1	1446	2	0	8	717	7	1	2	253643
AGGF		3000	EDD	16	1	50	1	0	2	16	2	1	1	246
WCEDD				12	1	136	1	0	3	13	3	1	1	1767
IMR				758	1	1372	2	0	10	696	11	1	2	236403
AGGF			SPT	15	0	53	1	0	1	15	1	0	1	278
WCEDD				12	1	105	1	0	2	12	3	1	1	1047

The WIP levels for each work center with all OR mechanism at intermediate DF are given in Table 3.54. This means, in such a system, an operation of an order have two alternative machines to be processed at one of them. From Table 3.54., it is noticeable that IMR OR mechanism results in a huge amount of average WIP with WC 1, WC 3, and WC 7. Note that, in most manufacturing environments such amount of WIP is impractical due to space limitations. DR has significant effect on the average WIP with IMR OR mechanism whereas PSP size has no significant effect on the average WIP with IMR OR mechanism.

One of the most noticeable results is that changing from low to intermediate DF, there is no bottleneck WC with both AGGWNQ and WCWT OR mechanisms. Also, average WIP across the WCs with both OR mechanisms is very well balanced. Both OR mechanisms' average WIP across WCs are not affected by PSP size but slightly affected by DR. However, this effect can be ignored. Average WIP levels across the WCs with both OR mechanisms are all practical. However, AGGWNQ OR mechanism give the best results if less and also very well balanced average WIP across the WCs is desired as the PSP size and DR changes.

Table 3.54. Average WIP levels with all OR mechanisms at Intermediate DF

OR Mec.	DF	PSP Size	DR	Work Centers										Var of WIP
				1	2	3	4	5	6	7	8	9	10	
IMR				119	145	130	111	154	142	113	114	136	146	251.65
AGGF			FIFO	11	13	12	10	13	12	10	11	12	13	1.34
WCEDD				13	15	14	12	16	15	12	13	15	15	2.00
IMR				72	87	78	65	91	84	67	68	81	87	88.22
AGGF		1000	EDD	11	13	12	10	13	12	10	11	12	13	1.34
WCEDD				13	15	14	12	16	15	12	12	14	15	2.18
IMR				105	125	114	101	105	92	93	96	102	113	105.36
AGGF			SPT	10	11	10	9	12	11	9	9	11	12	1.38
WCEDD				10	12	11	9	13	12	10	10	12	12	1.66
IMR				119	145	130	111	154	142	113	114	136	146	251.65
AGGF			FIFO	11	13	12	10	13	12	11	11	12	13	1.07
WCEDD				13	15	14	12	16	15	13	13	15	16	1.96
IMR				72	87	78	65	91	84	67	68	81	87	88.22
AGGF	1	2000	EDD	11	13	12	10	13	12	10	11	12	13	1.34
WCEDD				13	15	14	12	16	15	12	12	14	15	2.18
IMR				105	125	114	101	105	92	93	96	102	113	105.36
AGGF			SPT	10	11	10	9	12	11	9	10	11	12	1.17
WCEDD				11	12	11	10	14	12	10	10	12	13	1.83
IMR				119	145	130	111	154	142	113	114	136	146	251.65
AGGF			FIFO	11	13	12	10	13	12	11	11	12	13	1.07
WCEDD				13	15	14	12	16	15	13	13	15	16	1.96
IMR				72	87	78	65	91	84	67	68	81	87	88.22
AGGF		3000	EDD	11	13	12	10	13	12	10	11	12	13	1.34
WCEDD				13	15	14	12	16	15	12	12	14	15	2.18
IMR				105	125	114	101	105	92	93	96	102	113	105.36
AGGF			SPT	10	10	10	10	10	10	10	10	10	10	0.00
WCEDD				11	12	11	10	14	12	10	10	12	13	1.83

The WIP levels for each work center with all OR mechanism at high DF are given in Table 3.55. This means, in such a system, an operation of an order has three alternative machines to be processed at one of them. Average WIP results at high DF are consistent with the results at intermediate DF with one noticeable difference. That is, changing from intermediate to high DF a more balanced average WIP levels across the WCs is obtained especially with AGGWNQ OR mechanism.

Table 3.55. Average WIP levels with all OR mechanisms at High DF

OR Mec.	DF	PSP Size	DR	WC 1	WC 2	WC 3	WC 4	WC 5	WC 6	WC 7	WC 8	WC 9	WC 10	Var of WIP
IMR				132	137	117	129	129	150	134	119	130	144	101.43
AGGF			FIFO	12	12	11	12	12	13	12	11	12	13	0.44
WCEDD				15	16	13	15	15	17	16	14	15	17	1.57
IMR				80	83	71	78	77	91	82	72	78	88	40
AGGF		1000	EDD	12	12	12	12	12	12	12	12	12	12	0.00
WCEDD				14	15	13	14	14	16	15	13	14	16	1.16
IMR				109	115	103	105	102	119	102	98	103	118	55.37
AGGF			SPT	10	10	9	9	9	11	10	9	10	11	0.62
WCEDD				12	12	10	11	11	13	12	11	11	13	0.93
IMR				132	137	117	129	129	150	134	119	130	144	101.43
AGGF			FIFO	12	12	11	12	12	13	12	11	12	13	0.44
WCEDD				15	16	13	15	15	17	16	14	15	17	1.57
IMR				80	83	71	78	77	91	82	72	78	88	40
AGGF	2	2000	EDD	12	12	10	11	11	13	12	11	12	13	0.90
WCEDD				15	15	13	14	14	16	15	13	14	16	1.17
IMR				109	115	10	105	102	119	102	98	103	118	55.37
AGGF			SPT	10	10	9	9	9	11	10	9	10	11	0.62
WCEDD				12	12	10	11	11	14	12	11	12	13	1.29
IMR				132	137	117	129	129	150	134	119	130	144	101.43
AGGF			FIFO	12	12	11	12	12	13	12	11	12	13	0.44
WCEDD				15	16	13	15	15	17	16	14	15	17	1.57
IMR				80	83	71	78	77	91	82	72	78	88	40
AGGF		3000	EDD	12	12	10	11	11	13	12	11	12	13	0.90
WCEDD				15	15	13	14	14	16	15	13	14	16	1.17
IMR				109	115	103	105	102	11	102	98	103	118	55.37
AGGF			SPT	10	10	9	9	9	11	10	9	10	11	0.62
WCEDD				12	12	10	11	11	14	12	11	12	13	1.29

3.8. Conclusions

The MAPE performance measurement which stands for due date reliability is significantly affected by OR mechanism and DF. The presence of OR mechanisms that have a controlled release structure provide better MAPE performances at all levels of DF. Thus, it can be said that controlled release together with flexibility results in better due date reliability. But, it should be noted that changing from low to intermediate DF, MAPE performance with OR mechanisms that have controlled release structure deteriorate. However, changing from intermediate to high DF the best MAPE performance is attained with each OR mechanisms that have controlled release structure. Thus, at a certain DF the due date reliability of both AGGWNQ and WCWT OR mechanisms should be improved. It is interesting to observe that the levels of DF affect the MAPE performances of IMR OR mechanism in opposite direction. This can be attributed to controlled release structure. As a result, in terms of OR mechanism the best overall MAPE performance is attained with WCWT, in terms of DF the best overall MAPE performance is attained at high DF, in terms of PSP size the best overall MAPE performance is attained at low PSP size, and in terms of DR the best overall MAPE performance is attained with FIFO DR.

The MLT performance measurement which stands for delivery speed is significantly affected by OR mechanism and DF. The presence of OR mechanisms that have a controlled release structure provide better MLT performances regardless of DF. The results related to MLT performance reveals that introduction of ORR reduced not only SFTTs but also MLTs. Note that these results are not consistent with the many studies in related literature (e.g., Melnyk and Ragatz (1989)). This can be partly attributed to controlled queue of jobs in PSP. However, ORR reduces MLTs where no control is exercised over PSP. For example, from Table 3.6, it is seen at intermediate PSP size no control on queue of jobs in PSP is exercised. In this case, MLT performances of both AGGWNQ and WCWT OR mechanisms outperform the MLT performance IMR OR mechanism. But, note that reduced MLT with both AGGWNQ and WCWT exacted a price in the form of poorer MAPE and AT performances. Contrary to literature AGGWNQ and WCWT OR mechanisms with FIFO DR reduce MLTs. IMR OR mechanism with EDD and SPT DRs gives the best MLT performance at intermediate and high DF. In this case, note that the improvement in MLT performance is more than offset by poorer MAPE performance. As a result, in terms of OR mechanism the best overall MLT performance is attained with WCWT, in terms of DF the best overall MLT performance is attained at intermediate DF, in terms of PSP size the best overall MLT performance is attained at low PSP size, and in terms of DR the best overall MLT performance is attained with FIFO DR.

The best SFTT performance is attained with AGGWNQ and WCWT OR mechanisms regardless of DF. The compelling reason for this situation is predetermined WLL of AGGWNQ and WCWT OR mechanisms. Predetermined WLL of each OR mechanism provides stationary queue length at each machine on the shop floor. Also, stationary queue lengths result in manageable SFTTs. Note that, the length of SFTT can be adjusted by changing the WLL. As a result, in terms of OR mechanism the best overall SFTT performance is attained with AGGWNQ, in terms of DF the best overall SFTT performance is attained at intermediate DF, in terms of PSP size the best overall SFTT performance is attained at low PSP size, and in terms of DR the best overall SFTT performance is attained with SPT DR.

As known, IMR OR mechanism releases orders immediately as they arrive to the shop. Thus, it is not surprising that the best APWT performance is attained with IMR OR mechanism. Interaction between DF and other OR mechanisms significantly affects the APWT performance. The best APWT performance of AGGWNQ and WCWT OR mechanisms is attained at intermediate DF. As a result, in terms of OR mechanism the best overall APWT performance is attained with IMR, in terms of DF the best overall APWT performance is attained at intermediate DF, in terms of PSP size the best overall APWT performance is attained at low PSP size, and in terms of DR the best overall APWT performance is attained with SPT DR.

The best AT performance is attained with IMR OR mechanism at all levels of DF. But, as DF increases the gap between AT performances of OR mechanisms decreases. Note that, at high DF the AT performances of all OR mechanisms are nearly the same. Thus, it can be said that higher DF narrows the gap between AT performances of OR mechanisms. As a result, in terms of OR mechanism the best overall AT performance is attained with IMR, in terms of DF the best overall AT performance is attained at high DF, in terms of PSP size the best overall AT performance is attained at high PSP size, and in terms of DR the best overall AT performance is attained with FIFO DR.

The best AWQT performance is attained with AGGWNQ and WCWT OR mechanisms regardless of DF. The compelling reason for this situation is predetermined WLL of AGGWNQ and WCWT OR mechanisms. Predetermined WLL of each OR mechanism provides stationary queue length at each machine on the shop floor. Also, stationary queue lengths result in constant AWQTs. Note that, the length of AWQT can be adjusted by changing the WLL. Note that, the AQWT performance of shop is in line with SFTT performance as it is expected. As a result, in terms of OR mechanism the best overall AQWT performance is attained with AGGWNQ, in terms of DF the best overall AQWT performance is attained at intermediate DF, in terms of PSP size the best overall AQWT performance is attained at low PSP size, and in terms of DR the best overall AQWT performance is attained with EDD DR.

The levels of DF significantly affects T (%) performance of all OR mechanisms. It is interesting to observe that the worst T (%) performance is obtained with IMR OR mechanism at low DF whereas at high DF the best T (%) is attained with IMR OR mechanism. Thus, DF stands IMR OR mechanism in good stead in terms of T (%) performance. As DF increases the T (%) performance with WCWT deteriorates. At low and intermediate DF the best T (%) is attained with AGGWNQ OR mechanism. In this respect, it is very difficult to evaluate the interaction effect of DF and OR mechanisms. As a result, in terms of OR mechanism the best overall T (%) performance is attained with AGGWNQ, in terms of DF the best overall T (%) performance is attained at intermediate DF, in terms of PSP size the best overall T (%) performance is attained at low PSP size, and in terms of DR the best overall T (%) performance is attained with EDD DR.

DF and OR mechanism interaction has significant effect on M performance. M performance with AGGWNQ and WCWT significantly improves at higher DFs. As a result, in terms of OR mechanism the best overall M performance is attained with WCWT, in terms of DF the best overall M performance is attained at high DF, in terms of PSP size the best overall M performance is attained at high PSP size, and in terms of DR the best overall M performance is attained with EDD DR.

DF and OR mechanism interaction has significant effect on R performance. R performance with AGGWNQ and WCWT significantly improves at higher DFs. As a result, in terms of OR mechanism the best overall R performance is attained with IMR, in terms of DF the best overall R performance is attained at high DF, in terms of PSP size the best overall R performance is attained at high PSP size, and in terms of DR the best overall R performance is attained with SPT DR.

Consequently, it is very difficult to analyze all these conflicting performance measures together. As seen, there are trade-offs between some performance measurements. However, it is apparent that OR mechanisms that have controlled release structure improves some major measures of performances which IMR even does not take into account. Moreover, the most outstanding benefits of OR mechanisms is to control queues at each work center. For example, IMR mechanism results in impractical WIP levels at all levels of DF. But, AGGWNQ and WCWT results in acceptable WIP levels across work centers at low DF and very well-balanced WIP levels at intermediate and high DF. Note that, DF is a vital necessity for well balanced WIP levels. As the DF increases only marginal improvements observed in balance of WIP levels across work centers with AGGWNQ and WCWT whereas it is significantly improves with IMR (see Tables 3.53-3.55).

CHAPTER 4

GENETIC PROGRAMMING BASED DATA MINING APPROACH TO DISPATCHING RULE SELECTION IN A SIMULATED JOB SHOP

In this chapter, a genetic programming based data mining approach is used to compare and\or develop scheduling rules which will result in competitive shop performance under a given set of shop parameters (e.g., interarrival times, PSP length). The main purpose is to adopt the appropriate conventional dispatching rules (i.e., FIFO, SPT, and EDD) according to the current shop parameters dynamically. In order to achieve this, full factorial experiments are carried out to determine the effect of input parameters on predetermined performance measures. Afterwards, a new genetic programming based data mining tool that is known as MEPAR-miner (Multi-expression programming for classification rule mining) is used to extract knowledge on the selection of best possible conventional dispatching rules according to the current system status. The results revealed that the extracted rules are capable of selecting the appropriate dispatching rules according to the current shop parameters. All of the results are illustrated via numerical examples and experiments on simulated data.

4.1. Introduction

Scheduling operations on machines (servers) such that their completion time variance is minimized has applications in any service or manufacturing setting whenever it is desirable to provide jobs (customers) the same level of service, i.e., each customer spends approximately the same time in the system or waits for service the same time (Al-Turki et al., 2004). The scheduling problem in a job shop is the selection of the next job, among pending jobs at each station's queues, to be processed on each of the machine placed in each station in the shop to optimize a desired performance objective. Selection of a job from a set of pending jobs is made by making use of different ways such as optimization techniques, artificial intelligence algorithms and dispatching heuristics. Although optimization techniques can dispatch the jobs optimally with respect to the selected performance criterion, it has been shown that the job shop scheduling problem is NP-hard (Garey et al., 1976). Optimization techniques are, therefore, practical only for very small job shop problems. For example, a problem of scheduling as few as 10-jobs on a 10-machine job shop has proved very difficult to solve optimally (Muth and Thompson, 1963). On the other hand, due to having a static solution methodology, optimization techniques can not process new job arrivals and can not react to other disruptions without need to re-schedule. In this manner, optimization techniques are not on-line scheduling methods which make them impractical in real life applications.

The computational complexity of job shop scheduling has stimulated interest in heuristics, meta-heuristics and other algorithms for solving large job shop problems in a reasonable computational time. One class of heuristics includes the dispatching rules (DR). DRs are often favored because of their simplicity, ease of application and the fact that they are an on-line scheduling method that can be used in real-time scheduling. This makes them dynamic in the sense that they can process new job arrivals and react to other disruptions without need to re-schedule (Al-Turki et al., 2004). In this sense, DRs work well for dynamic scheduling problems. However, dispatching rules' main disadvantage is that they can not adapt themselves to changing system conditions which causes to deteriorate their performance measurement for which they have been developed.

Due to this fact, there exists a trade-off between solution quality and efficiency in scheduling problems. The trade-off between solution quality and efficiency can be balanced by selecting the most appropriate dispatching rule for the current shop parameters among a set of dispatching heuristics. By this way, still the dispatching heuristic does not adapt itself to the changing shop conditions but adoption of the most appropriate dispatching heuristic by switching between a set of dispatching heuristics according to the current shop parameters is provided. By this way, the deterioration of the selected performance measurement's value can be prevented. As a result, this study seeks better satisfaction of selected performance measurements by applying a genetic programming based data mining approach that is known as multi-expression programming for classification rule mining for selecting appropriate dispatching rules according to the current job shop parameters.

4.2. Literature Review

Research into DRs appears to take two main directions. The first uses simulation to evaluate new and existing dispatching rules under different shop conditions and performance objectives (Kıran and Smith, 1984, Waikar et al., 1995, Chang et al., 1996). The second direction aims to improve the performance of existing rules by using new tools or strategies to support or hybridize existing rules (Al-Turki et al., 2004). Dynamic scheduling of manufacturing systems has primarily involved the use of DRs. Within the context of conventional job shops, the relative performance of these rules has been found to depend upon the system attributes, and no single rule is dominant across all possible scenarios. This indicates the need for developing a scheduling approach which adopts a state-dependent DR selection policy (Shaw et al., 1992). By other words, the problem of selecting the best DR for a given performance measurement under different levels of input parameters (system attributes) arises (i.e., arrival rate). In fact, this problem continues to be a very active area of research (Jones and Rabelo, 2007).

Pierreval and Mebarki (1997) proposed a scheduling strategy which is based on a dynamic selection of certain pre-determined dispatching rules. A new selection is carried out each time a machine becomes available, depending on: (1) primary and secondary performance objectives; (2) operating conditions; (3) an analysis of the system state which aims at detecting particular symptoms from the numerical values taken by state variables. This selection method is improved through the optimization of the numerical thresholds used in the detection of symptoms. A simple heuristic dispatching strategy has been designed based on this dynamic selection approach. El-

Bouri and Shah (2006) proposed an intelligent system that selects dispatching rules to apply locally for each machine in a job shop. Randomly generated problems are scheduled using optimal permutations of three different dispatching rules on five machines. A neural network is then trained to associate between statistical characterizations of the job mix in each of these problems, with the best combination of dispatching rules to use. Holthaus and Rajendran (1997) developed new scheduling rules based upon the combination of well-known rules. The results of the simulation study reveal that the simple structured combination rules are quite efficient. Li and Olafsson (2005) showed that by using decision tree models to learn from properly prepared data set, not only a predictive model that can be used as a dispatching rule can be obtained, but they also they showed that previously unknown structural knowledge can be obtained that provides new insights and may be used to improve scheduling performance. Wang et al. (2005) developed a hybrid knowledge discovery model, using a combination of a decision tree and a back-propagation neural network, to determine an appropriate dispatching rule, for use in the semiconductor final testing industry in order to achieve high manufacturing performance. They used production data with noise information, and predicted its performance. Chiang and Fu (2007) discussed the use of dispatching rules to solve job shop-scheduling problems concerning due date-based criteria. Eighteen existing rules that were popularly adopted for due date-based objectives examined in terms of their advantages and the core design concepts inside them. Then, a rule that combines three key design concepts including ‘shorter processing time earlier’, ‘earlier due date earlier’ and ‘longer remaining processing time earlier’ in order to generate schedules with a good and balanced performance on multiple due date-based objectives were proposed. Giannelos et al. (2007) discussed the tools used in the characterization of a chaotic or nonlinear system for studying the performance of dispatching policies in manufacturing systems. They studied and analyzed the results of a simulated simple manufacturing system in which common dispatching rules were used with the help of time-delay plots. Then, they proposed a new method of scheduling according to the conclusions drawn from time-delay plots. Shaw et al. (1992) developed a scheduling approach which employs inductive learning to generate pattern-directed heuristics for making dynamic scheduling decisions in an FMS. Their approach comprises the three steps of: 1) Generation of training examples through experimentation involving various dispatching rules; 2) determination of selection heuristics through inductive learning; and 3) executing pattern-directed scheduling adaptively.

4.3. Problem Definition

Dispatching rules have been classified mainly according to the performance criteria for which they have been developed. By other words, dispatching rules are problem dependent. For example, in the study of Subramaniam et al. (2000), it was pointed out that SPT dispatching rule was superior to other simple dispatching rules for performance measures based on job completion times (e.g., Kıran and Smith (1984)) due to its effect of getting machines to work quickly. But, it performs well under tight load conditions (Holthaus and Rajendran, 1997). Baker (1984b) studied the impact of the tightness of the due-date on mean tardiness. He showed that, the EDD rule is superior when the due dates are set loosely, and the SPT rule performs well when the due dates are set tightly. Also, he showed that the Modified Operation Due Date (MOD) rule has the best tardiness performance in the case of setting the due date not at the extremes (i.e., loose or tight). Thus, right dispatching rule must be chosen to apply for a given job shop problem for better satisfaction of the performance criterion. So, for a specific performance measurement one has to determine which dispatching rule to employ when the system faces different combination of input parameters. The difficulty, of course, lies in knowing in advance which rule is the best to employ. An approach that would help is to identify special characteristics or conditions in job shop problems, and associate these with specific dispatching rules that have been observed in the past to perform best in similar problems (Al-Turki et al., 2004).

This study aims at selecting the most suitable dispatching rule with respect to a specific performance measurement under changing input parameter levels (e.g., arrival rate, buffer size etc.). In order to achieve this aim, we first determined factors (input parameters) to identify the behavior of the system under different levels of them. The response variables were selected as average total flowtime (F_{avg}), percent of tardy jobs (T%), and average tardiness (T_{avg}). Since, sophisticated rules hardly provide significant improvement over less sophisticated ones simple and easy to implement dispatching rules were selected (Anderson, and Nyirenda, 1990). The selected dispatching rules were first in first out (FIFO), shortest processing times (SPT), and earliest due date (EDD). The present problem is to find classification rules which can classify different factor levels into to selected DRs by using the MEPAR-miner algorithm (Baykasoğlu and Özbakır, 2007). Afterwards, the most appropriate dispatching rule is dynamically adapted according to the current system status by switching between FIFO, SPT, and EDD dispatching rules.

4.4. A Brief Overview of the MEPAR-Miner Algorithm

Baykasoğlu and Özbakır (2007) have recently proposed a new data mining algorithm which is based on Multi-Expression Programming (MEP). This algorithm is known as MEPAR-miner (Multi-Expression Programming for Association Rule Mining). In the following, we briefly review some of the basic concepts of MEPAR-miner algorithm. In MEPAR-miner the main structure of the rule list and its utilization is as follows:

IF antecedent$_1$ THEN class1
ELSE IF antecedent$_2$ THEN class2
. . .
ELSE class default

The evaluation of rule list is started from the topmost rule and performed towards the default class until the instance exactly matches the corresponding rule. In the case that none of the rules in the list of rules matches a new instance, the new instance will be classified as the default class. The default class is determined to be as the largest class in the data set.

Function and terminal sets: In MEPAR-miner algorithm the function set consists of mathematical and logical operators. The terminal set consists of attribute, Relational Operator (RO) and value of corresponding attribute which is assigned from the domain of related attribute. Relational operators are dependent on the type of attribute (categorical, continuous). Function and terminal sets can be summarized in a tabular format as in Table 4.1.

Table 4.1. Function and terminal sets (adapted from Baykasoğlu and Özbakır, 2007)

X_i	i^{th} attribute
Relational operator	Type of attribute
=, ≤, ≥	Categorical attributes Continuous attributes
V_{xi}	Domain of i^{th} attribute
Terminal Set	$\{x_0 - RO - V_{x1}, .., x_n - RO - V_{xn}\}$
Function Set	{AND, OR, NOT}

Arguments of a logical operator cannot point the same gene in the chromosome in order to avoid redundant rules. As an example assume that:

$$F \rightarrow \{AND, OR, NOT\},\ RO \rightarrow \{\leq, \geq, =\},\ T \rightarrow \{x_0, x_1, x_2\}$$

As shown in Figure 4.1, each gene in the chromosome represents the antecedent part of logical expression. So, the number of logical expressions is equal to the length of the chromosome. Gene 7 in Figure 4.1 represents the following logical expression:

$$\text{IF } ((x_1 \geq 8) \text{ AND } (x_2 = 1)) \text{ OR } ((x_0 \leq 5) \text{ OR } (x_2 = 1)) \text{ THEN Class}_i$$

Consequent of the logical expression is evolved concurrently with the rule set to provide flexibility and possibility of producing good sets of rules. Determination of the constant consequence at the beginning will lead to good classification rules with different consequents. So, each gene in the chromosome is evaluated with respect to all different consequences in the data set. The consequent which results in the best fitness value is determined as the class label of the corresponding gene. After fitness evaluation, each expression (gene) has its own fitness value and class label. The best expression represents the chromosome. Fitness value and consequent of the chromosome are set to fitness value and consequent of the best expression.

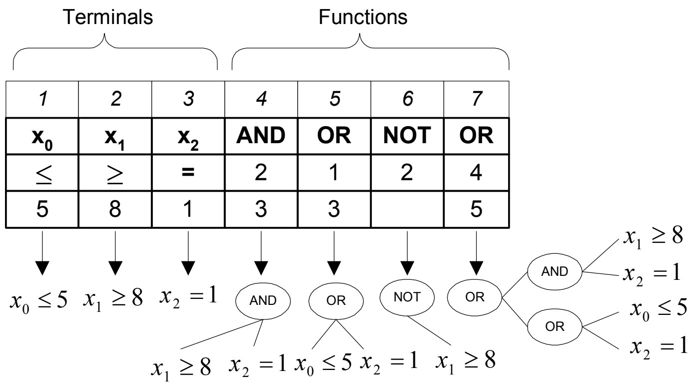


Figure 4.1. Sample chromosome structure for classification rule (adapted from Baykasoğlu and Özbakır, 2007)

Initial population: Note that Figure 4.1 is a sample chromosome. Population size parameter which is known previously determines the number of chromosomes in the population. Each chromosome in the population (i.e., individuals of population) is constructed according to the following procedure, repeatedly:

The numbers of terminal genes which are positioned in the first location of chromosomes are determined to be the number of attributes in the classification problem. Each terminal gene has two pointers one for relational operator which is assigned randomly from RO set and the other for attribute value domain which is assigned randomly from the corresponding attribute’s value domain. After these two assignments the terminal gene is completed. From Figure 4.1 it is seen that the second part of the chromosome consists of logical functions. In the second part, each gene is constructed by assigning a function randomly from logical function set. According to the assigned function, argument pointer(s) is generated for the purpose of pointing to the preceding genes in the chromosome. AND, OR operators have two argument pointers while NOT operator has one.

Fitness function: Four possibilities exist when a rule is used to classify a given training instance:

1. True positive (TP) : The rule predicts that the class is yes and the class of given instance is indeed yes.

2. True negative (TN) : The rule predicts that the class is no and the class of given instance is indeed no.

3. False positive (FP) : The rule predicts that the class is yes but the class of the given instance is no.

4. False negative (FN) : The rule predicts that the class is no but the class of the given instance is yes.

Considering these possibilities fitness function is calculated by multiplying fraction of actual positive examples that are correctly classified by fraction of negative examples that are correctly classified. Fitness = $[TP/(TP+FN)]$ x $[TN/(TN+FP)]$ = $S_e x S_p$. The fitness value is 1 when all of the instances are correctly classified by the rule.

Genetic operators: Two genetic operators used within MEPAR-miner algorithm are crossover and mutation.

Elitization: First of all, the chromosome with the best fitness value in population is copied to the next generation without any change.

Selection: Binary tournament selection procedure is used to fill the mating pool. Two individuals are selected randomly from the current population. The best individual is copied to the mating pool.

Crossover: Two parents are selected from the mating pool and recombined according to the predefined crossover probability (p_m) during crossover (one point crossover). A crossover point is randomly determined to perform the recombination process as shown in Fig. 2. The first part of parent-1 and the second part of parent-2 are recombined to produce offspring-1. Offspring-2 is obtained by applying the same replacement in reverse order.

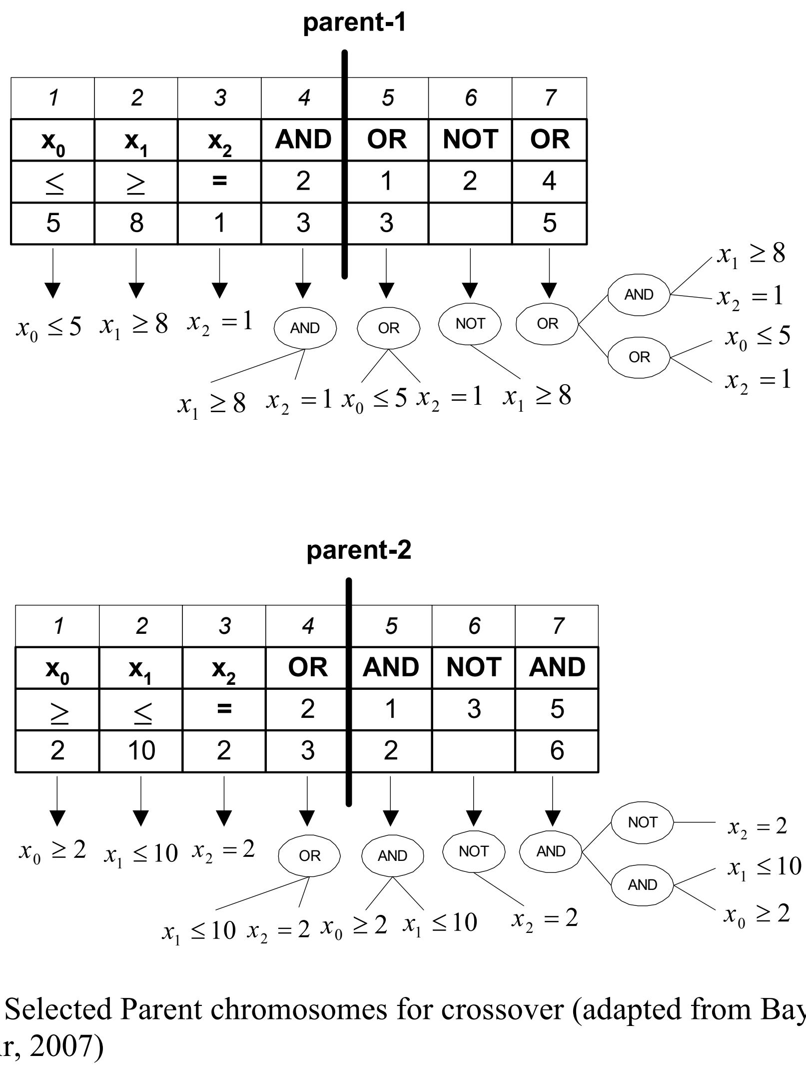


Figure 4.2. Selected Parent chromosomes for crossover (adapted from Baykasoğlu and Özbakır, 2007)

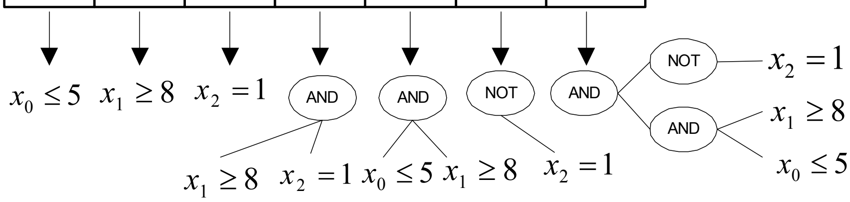
Note that the crossover point is selected randomly as the 4th position of the parent chromosomes which is shown by a bold vertical line. For example, gene 7 in the parent chromosomes represents the following rules before crossover operation.

Gene 7 of parent-1: IF (($x_1 \geq 8$) AND ($x_2=1$)) OR (($x_0 \leq 5$) OR ($x_2=1$)) THEN $Class_i$

After crossover, two offspring are obtained as shown in Figure 4.3.

offspring-1

1	2	3	4	5	6	7
x_0	x_1	x_2	AND	AND	NOT	AND
$\leq$	$\geq$	=	2	1	3	5
5	8	1	3	2		6



offspring-2

1	2	3	4	5	6	7
x_0	x_1	x_2	OR	OR	NOT	OR
$\geq$	$\leq$	=	2	1	2	4
2	10	2	3	3		5

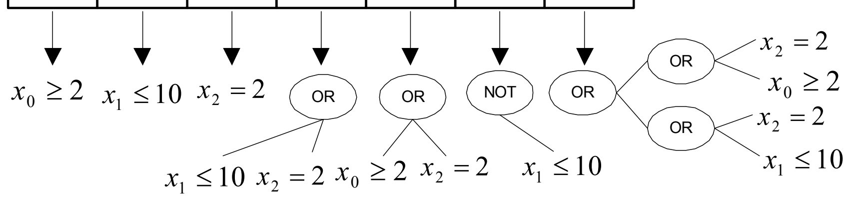


Figure 4.3. Offspring after crossover (adapted from Baykasoğlu and Özbakır, 2007)

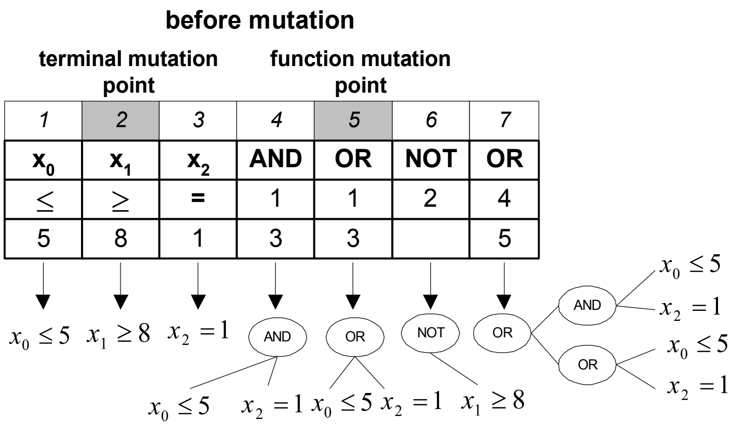
For example, gene 7 of offspring-1 represents a completely different decision rule from their parents.

Gene 7 of offspring-1: IF (($x_0 \leq 5$) AND ($x_1 \geq 8$)) AND (NOT ($x_2 = 1$)) THEN $Class_i$

Mutation: Target of the mutation operator may be terminal pointer, function, and function pointer. By mutation, some randomly selected mutation point(s) (gene(s)) within the chromosome is/are changed according to a predefined mutation probability. If a terminal gene is determined to be mutated first terminal pointers are replaced by another relational operator and then the attribute value is modified accordingly to be within the domain range. If a function gene is determined to be mutated first logical function is replaced by randomly selected another logical function. The pointers of mutated logical function which point to the preceding genes are reassigned. An illustrative example of mutation operation which is taken from [20] is shown in Figure 4.4. Logical expressions represented by gene 5 before and after mutations are as follow:

Gene 5 before mutation: IF ($x_0 \leq 5$) OR ($x_2 = 1$) THEN $Class_i$

Gene 5 after mutation: IF ($x_1 \leq 10$) AND ($x_2 = 1$) THEN $Class_i$



after mutation

1	2	3	4	5	6	7
x_0	x_1	x_2	AND	AND	NOT	OR
$\leq$	$\leq$	=	1	2	2	4
5	10	1	3	3		5

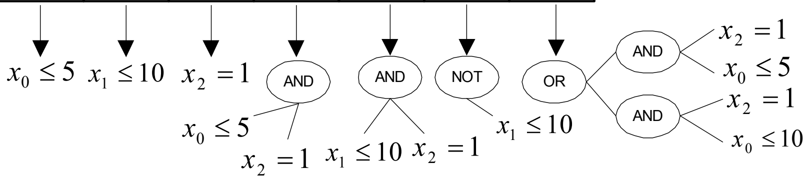


Figure 4.4. Chromosome before and after mutation operation (adapted from Baykasoğlu and Özbakır, 2007)

4.5. Simulation Study

Simulation experiments are conducted on a hypothetical job shop to collect data for different levels of input parameters and selected response variables. Then, collected data is used as input to MEPAR-miner algorithm for testing and training.

The simulation model represents a multi-stage job shop production system containing 24 workstations. There is only one machine in each workstation. The arrival of jobs to the system is assumed to be random with exponentially distributed interarrival times. The system was observed for three different levels of the interarrival time attribute, 1.5, 3, and 4.5 time units, respectively. The total number of operations of a job is assigned at the arrival time of the job by generating a random number between 1 and 10. Thus, the total number of operations of a job can be between 1 and 10. Also, routes of the jobs are determined according to the uniformly determined operation sequence. For example, if the total number of operations of an arriving job is assigned to be 3, a random number between 1 and 24 is generated and assigned as its first operation no and a second one generated and assigned as its second operation no, and the third one generated and assigned as its third operation no. Note that, in the current job shop environment each job can require one or more of the 24 possible operations to be completed (see Table 4.2). Each machine can process only predetermined operations and also one operation at a time (see Table 4.2). A given machine could appear more than once in a job's routing even for consecutive operations. The processing times of each job are assumed to be uniformly distributed. Operation processing times according to the stations is given in Table 4.2. Transportation times are assumed to be negligible. The simulation model is run for 18000 finished jobs and after preliminary runs 8000 time unit is determined to be warm-up period to avoid incorporation of transient behavior of the system. The experiments are performed using 5 replications of each selected dispatching rule and the developed composite dispatching rule, thus minimizing variability in the results. Common random numbers are used to provide the same experimental condition across the runs for each factor combination.

All arriving jobs are waited in an entrance pool according to the FIFO dispatching rule. In the case of exceeding the capacity of entrance pool, arriving jobs are rejected (see Table 4.3 for the levels of entrance pool capacity). Due dates of the jobs are assigned by using the conventional total work content (TWK) due date assignment rule. Three levels of the due date tightness parameter, tight, medium, and loose due dates are determined, by letting the due date tightness factor differentiate between 30, 50, and 75 (see Table 4.3 for the levels of the due date tightness). Before releasing a job to the shop floor, the entrance pool is searched. The search is made according to the search dept of queue (SDEPQ) parameter (see Table 4.3 for the levels of the SDEPQ parameter). For example, if the current level of the SDEPQ is 25 (i.e., level 1), only the first 25 jobs from the entrance pool will be checked whether there exist any mature jobs. In the case of being mature they released to the shop floor otherwise they kept waiting in the entrance pool. In order to be a mature job, the number of waiting jobs in each workstation's queue placed in the job's route must be lower than the buffer size (BUFSIZ) parameter's value (see Table 4.3 for the levels of the BUFSIZ attribute). For example, consider a job requires processing of the operations 3, 7, and 11 respectively to be finished. Note that, from Table 4.2 it is seen that these operations can only be processed by workstation 20, 1, and 11 which is also known to be the job's route. In this case, whenever a search takes place whether to release the job to the shop floor, the number of jobs waiting in each workstation queue on the job's route must be equal or lower than the current BUFSIZ parameter's value (i.e., 50). If this condition is met then the job is released to the shop floor otherwise it must be kept waiting in the entrance pool. Then, the SDEPQ parameter's value is increased by 1 whether the next job is released to the shop floor or not. If the value of SDEPQ parameter is lower than its predetermined level (i.e., 25), checking for subsequent jobs waiting in the entrance pool is performed. As a result, the decision whether to release or not to release the job to the shop floor depends on the number of jobs, in each queue placed on job's route. If the number of jobs in each queue placed on job's route is lower than the current BUFSIZ parameter's value then release the job to the shop floor otherwise the job must be kept waiting in the entrance pool. The search goes on like in this manner until the current level of SDEPQ input parameter is reached.

After, verification and validation of the simulation model, it is run for all the input parameter combinations. Then, data related to three selected performance measurements (i.e., response variables) (F_{avg}, T%, and T_{avg}) for each dispatching rule (SPT, EDD, FIFO) is gathered. Consequently, the test and training data are ready for the composite dispatching rule extraction and verification of the extracted ones.

4.5.1. Performance measures

Three performance measurements (i.e., F_{avg}, T%, and T_{avg}) are considered. The main concern is to observe whether the extracted rule (i.e., composite dispatching rule) can perform better than the conventional dispatching rules with respect to selected performance measurements. For example, from the literature, it is well known that SPT gives the best performance with respect to F_{avg} performance criteria. So, one of our aim is to show whether the developed composite dispatching rule performs as well as SPT dispatching rule with respect to F_{avg} performance measure under different shop conditions.

Table 4.2. Processing times of operations according to stations

Operation No	Station No	Process Time	Operation No	Station No	Process Time
1	9	U(15,20)	13	4	U(12,20)
2	10	U(12,18)	14	5	U(15,20)
3	20	U(12,18)	15	6	U(12,18)
4	21	U(12,18)	16	12	U(15,20)
5	17	U(15,20)	17	13	U(10,20)
6	16	U(10,15)	18	14	U(10,15)
7	1	U(15,20)	19	15	U(10,15)
8	8	U(12,18)	20	18	U(12,18)
9	7	U(10,15)	21	22	U(10,15)
10	3	U(15,25)	22	23	U(15,20)
11	11	U(15,20)	23	24	U(10,15)
12	2	U(10 15)	24	19	U(15,20)

4.5.2. Simulation experiments

Experiments are performed according to the full factorial design to detect the effects of input parameters on each selected performance measurement accurately. In the full factorial design, all possible combinations of the factors (i.e., input parameters) are considered to analyze the relationship between an individual factor and output. Due to the fact that the remaining factors are adjusted at a constant level while examination of a certain factor taking all possible values, the influence of this factor on the output can be analyzed exhaustively. Factors of experimental design and their levels are shown in Table 4.3.

Table 4.3. Factors and their levels

Factors	Levels		
	1	2	3
Interarrival times (INTARR) (unit time)	1.5	3	4.5
Entrance Pool Length (EPL) (jobs)	1000	3000	5000
Search depth of queue (SDEPQ) (jobs)	25	50	75
Buffer size (BUFSIZ) (jobs)	50	75	100
Due date tightness (DDTIGHT) (constant)	30	50	75

Since there are 5 factors, 3 levels for each, 243 (3^5) experiments are performed. These experiments are repeated for FIFO, SPT and EDD DRs to determine the selected performance measurements' values as the response variable's value desired to be minimized. For example, for the F_{avg} performance measurement, the DR which owns the minimum F_{avg} value constitutes the class attribute to generate the classification rules by using the MEPAR-miner algorithm. During the preprocessing of the data set, F_{avg}, T%, and T_{avg} results are found meaningless in two cases. After removing these cases, data set is shuffled randomly to ensure the homogeneity. The data set is divided into two parts, 1/3 and 2/3, for testing and training purposes, respectively. MEPAR-miner algorithm is applied on this data set for generating classification rules as a 3-class problem. Problem specifications and MEPAR-miner parameter settings are summarized in Table 4.4 for F_{avg} performance measurement. These specifications and settings are all the same for T% and T_{avg} measurements. MEPAR-miner algorithm is run for five times with the same parameter setting for each performance measurement. Four executions are resulted with 98,75% test accuracy and the remaining one with 95%. Mean accuracy for testing data is found as 98%. Afterwards, among these five runs, the best classification rules for each performance measurement are selected according to the classification rule's number of correctly classified test data performance. The best classification rule and their fitness values are listed in Tables 4.5-4.7 for F_{avg}, T%, and T_{avg} performance measurements, respectively. Default class is determined as 2 because SPT has the maximum number among all other classes in training data set.

Table 4.4. Parameter settings of MEPAR-miner

Training Data	161
Testing Data	80
Output	Average Total Flowtime (F_{avg})
Problem Attributes	
X_0	Interarrival times
X_1	Pool release length
X_2	Search depth of queue
X_3	Buffer size
X_4	Due date tightness
Class Attribute	3 (0:FIFO, 1: EDD, 2, SPT)
MEPAR-miner Parameter Setting	
Generation Number	500
Population Size	200
Crossover	One-Point crossover
Crossover Probability	0.9
Mutation Probability	0.2
Chromosome Length	30(Attributes:5, Functions:25)
Fitness Function	S_e*S_p

Note that, Sensitivity (S_e) measures the fraction of actual positive examples that are correctly classified while specificity (S_p) measures the fraction of actual negative examples that are correctly classified.

4.6. The methodology

After generating data for training and testing, one rule set which consists of 5 rules is extracted for each objective function by using MEPAR-miner algorithm (objective functions: Vaues of F_{avg}, T%, and T_{avg}). Each objective function's rule set is tested and the best rule among the five rules is determined for each objective function. The best rules according to the objective functions are given in Tables 4.5, Table 4.6, and Table 4.7. Then, Extracted composite dispatching rules for each performance measurement (see Table 4.5-4.7) are tested with different levels of all input parameters. For this purpose 24 different factor combinations are selected randomly among 243 factor combinations. Simulation model is run by using each factor combination and for each performance measurement; results of the dispatching rules are summarized in Table 4.8-4.10.

Table 4.5. The best classification rule and fitness values for F_{avg}

Extracted Rule from MEPAR-miner	Fitness
IF NOT(((x_0<=3))and(((x_2<=50))and((x_3>=50)))) THEN class 2	0,661
ELSE IF ((((x_1>=3000))and(((x_1>=3000))and(NOT((x_0>=4.5))))) and((x_2<=25)))or(((x_3<=50))and(((x_1>=3000))and(NOT ((x_0>=4.5)))))THEN class 0	0,686
ELSE IF (((x_3<=50))and((x_0<=3)))or((((x_3<=50))and((x_2<=25)))or (((x_2<=25))and((x_0<=3)))) THEN class1	0,577
ELSE DEFAULT class 2 Correctly classified number of test data 79 out of 80	

Table 4.6. The best classification rule and fitness values for part of tardy jobs

Extracted Rule from MEPAR-miner	Fitness
IF ((x0>=3.00))and((((x2<=25.00))and((x4>=50.00)))and((x0>=3.00))) THEN class 0	0,872
ELSE IF ((((NOT((x4<=50.00)))and((x2<=75.00)))or((x0>=4.50)))and((((x0>=4.50)) or(((x1<=1000.00))or(((x4<=50.00))or((x1<=1000.00))))))and ((NOT(NOT((x4<=50.00))))or (NOT((x4<=50.00))))THEN class 1	0,714
ELSE IF ((((x4<=30.00))or((x3>=75.00)))and(((x4<=30.00))or (((x3>=75.00))and((x0<=3.00)))))and((((x2>=25.00)) and((((x3>=75.00))and((x0<=3.00)))or(((x0<=3.00))and (((x4<=30.00))or((x3>=75.00))))))or((x3>=75.00))) THEN class 2	0,757
ELSE DEFAULT class=2 Correctly classified number of test data 76 out of 80	

Table 4.7. The best classification rule and fitness values for average tardiness

Extracted Rule from MEPAR-miner	Fitness
IF ((((x1>=5000.00))and((x3<=75.00)))and((x4<=50.00))) and(((x2<=25.00)) and ((x0<=1.50))) THEN class 2	1
ELSE IF (((x0>=4.50))and(((x4>=50.00))or((x2>=50.00))))or ((NOT((x2>=50.00)))and(((((x3>=100.00))or((x0>=4.50)))or ((x0>=4.50)))and(NOT((x0>=4.50))))) THEN class 0	0,640
ELSE IF (NOT((NOT((x4<=30.00)))or((x1<=3000.00))))or ((((x4<=30.00))and((x3>=75.00)))or(NOT(NOT((x0<=3.00))))) THEN class 1	0,625
ELSE DEFAULT class 1 Correctly classified number of test data 75 out of 80	

Table 4.8. Results for F_{avg}

Test No	*IntArr*	*Prl*	*SDEPQ*	*BufSiz*	*DDTight*	*F_{avg} values*			
						Extracted Rule	*EDD*	*FIFO*	*SPT*
1	1,5	1000	25	50	30	5822	5940	6495	6061
6	1,5	1000	25	75	75	6354	6488	6859	6701
15	1,5	1000	50	75	75	6252	6209	6192	6214
36	1,5	3000	25	100	75	14217	14831	13476	14031
46	1,5	3000	75	50	30	10907	11070	10878	10741
57	1,5	5000	25	50	75	15861	17580	16081	15590
60	1,5	5000	25	75	75	16312	17328	16572	15954
73	1,5	5000	75	50	30	14453	14807	14556	14670
85	3	1000	25	75	30	5217	5423	5639	5308
88	3	1000	25	100	30	5482	5819	6006	5629
91	3	1000	50	50	30	4599	4768	4761	4674
113	3	3000	25	75	50	8638	9383	9453	8880
124	3	3000	50	100	30	7635	8050	7816	7654
137	3	5000	25	50	50	8278	9454	10009	8220
140	3	5000	25	75	50	9081	8635	10153	8428
150	3	5000	50	75	75	7182	7528	7080	6709
163	4,5	1000	25	50	30	949	938	1196	699
169	4,5	1000	25	100	30	822	977	917	562
190	4,5	3000	25	50	30	949	938	1196	699
197	4,5	3000	25	100	50	1005	1001	917	562
202	4,5	3000	50	75	30	868	880	861	572
209	4,5	3000	75	50	50	709	931	926	612
220	4,5	5000	25	75	30	923	971	938	687
234	4,5	5000	50	100	75	909	907	905	497

Table 4.9. Results for T%

Test No	*Int Arr*	*Prl*	*SDEPQ*	*Buf Siz*	*DD Tight*	*T% values*			
						Extracted Rule	*EDD*	*FIFO*	*SPT*
1	1,5	1000	25	50	30	0,8195	0,9327	0,9159	0,8260
6	1,5	1000	25	75	75	0,4264	0,4139	0,4917	0,4456
15	1,5	1000	50	75	75	0,3030	0,3027	0,3498	0,3171
36	1,5	3000	25	100	75	0,7577	0,9158	0,8291	0,7824
46	1,5	3000	75	50	30	0,8080	0,9466	0,8906	0,8101
57	1,5	5000	25	50	75	0,8383	0,9272	0,8574	0,8341
60	1,5	5000	25	75	75	0,8390	0,9422	0,8817	0,8366
73	1,5	5000	75	50	30	0,9145	0,9885	0,9586	0,9237
85	3	1000	25	75	30	0,6576	0,8802	0,8554	0,6814
88	3	1000	25	100	30	0,6545	0,8794	0,8618	0,6763
91	3	1000	50	50	30	0,4791	0,7487	0,6542	0,5331
113	3	3000	25	75	50	0,6888	0,7815	0,7370	0,6486
124	3	3000	50	100	30	0,5933	0,8611	0,8340	0,6366
137	3	5000	25	50	50	0,6481	0,7396	0,6788	0,6204
140	3	5000	25	75	50	0,6846	0,7830	0,7373	0,6279
150	3	5000	50	75	75	0,3784	0,4692	0,4262	0,3661
163	4,5	1000	25	50	30	0,0421	0,0504	0,1161	0,0513
169	4,5	1000	25	100	30	0,0421	0,1071	0,0767	0,0319
190	4,5	3000	25	50	30	0,0421	0,0504	0,1161	0,0513
197	4,5	3000	25	100	50	0,0170	0,0140	0,0275	0,0147
202	4,5	3000	50	75	30	0,0432	0,0440	0,0625	0,0307
209	4,5	3000	75	50	50	0,0210	0,0214	0,0291	0,0207
220	4,5	5000	25	75	30	0,0468	0,0744	0,0747	0,0480
234	4,5	5000	50	100	75	0,0112	0,0050	0,0112	0,0072

Table 4.10. Results for T_{avg}

Test No	*Int Arr*	*Prl*	*SDEPQ*	*Buf Siz*	*DD Tight*	*T_{avg} values*			
						Extracted Rule	*EDD*	*FIFO*	*SPT*
1	1,5	1000	25	50	30	3566	3691	4393	4486
6	1,5	1000	25	75	75	3022	3061	3667	4845
15	1,5	1000	50	75	75	4092	4749	4909	7667
36	1,5	3000	25	100	75	9001	9330	9135	10667
46	1,5	3000	75	50	30	8943	9138	9564	10468
57	1,5	5000	25	50	75	11072	12366	11994	11892
60	1,5	5000	25	75	75	11327	11898	12145	12312
73	1,5	5000	75	50	30	12228	12579	12725	13350
85	3	1000	25	75	30	3223	3351	3773	4673
88	3	1000	25	100	30	3515	3829	4167	5204
91	3	1000	50	50	30	3114	3254	3893	5222
113	3	3000	25	75	50	6272	7069	7768	8588
124	3	3000	50	100	30	6305	6639	6610	8950
137	3	5000	25	50	50	6601	7784	9505	8102
140	3	5000	25	75	50	6844	6242	8712	8352
150	3	5000	50	75	75	5270	5694	6316	8371
163	4,5	1000	25	50	30	1508	1628	1665	2558
169	4,5	1000	25	100	30	700	831	1267	4505
190	4,5	3000	25	50	30	1508	1628	1665	2558
197	4,5	3000	25	100	50	1895	1559	1355	7075
202	4,5	3000	50	75	30	1750	1935	1651	4487
209	4,5	3000	75	50	50	3778	4605	3715	5624
220	4,5	5000	25	75	30	1333	1196	1399	3232
234	4,5	5000	50	100	75	3176	3152	2001	9646

From Figure 4.5 and Table 4.8, it is seen that there is no significant difference between the developed composite DR (generated by the MEPAR-miner algorithm) and the conventional DRs in terms of the F_{avg} performance measurement. For some cases the composite dispatching rule's F_{avg} performance deteriorates slightly but in general its performance is better than the conventional rules. An interesting result is observed in the case of arrivals at infrequent intervals to the system (i.e., when the arrival rate is 4.5). In this case, SPT dispatching rule's F_{avg} performance dominates others (see experiment no 163….234 in Table 4.8). Other than this case, it can be said that the developed composite dispatching rule's F_{avg} performance is robust which means its performance is not system status dependent.

From Figure 4.6 and Table 4.9, it is seen that the developed composite dispatching rule's T% performance is better than others in most of the experiments. Therefore, it can be said that under most of the possible shop conditions, the proposed composite dispatching rule is able to provide the best possible performance for T%.

From Figure 4.7 and Table 4.10, it is also seen that the developed composite dispatching rule dominates others in most of the experiments in terms of T_{avg} performance measurement. It can also be said that under most of the possible shop conditions, the developed composite dispatching rule is able to provide the best possible performance for the T_{avg} performance measure.

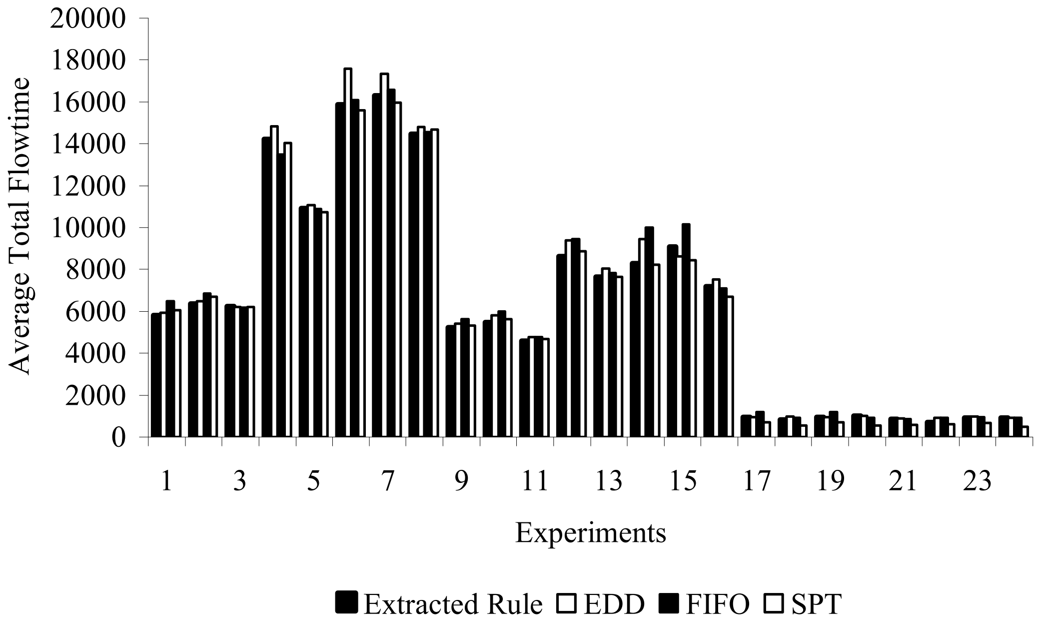


Figure 4.5. F_{avg} results with respect to dispatching rules

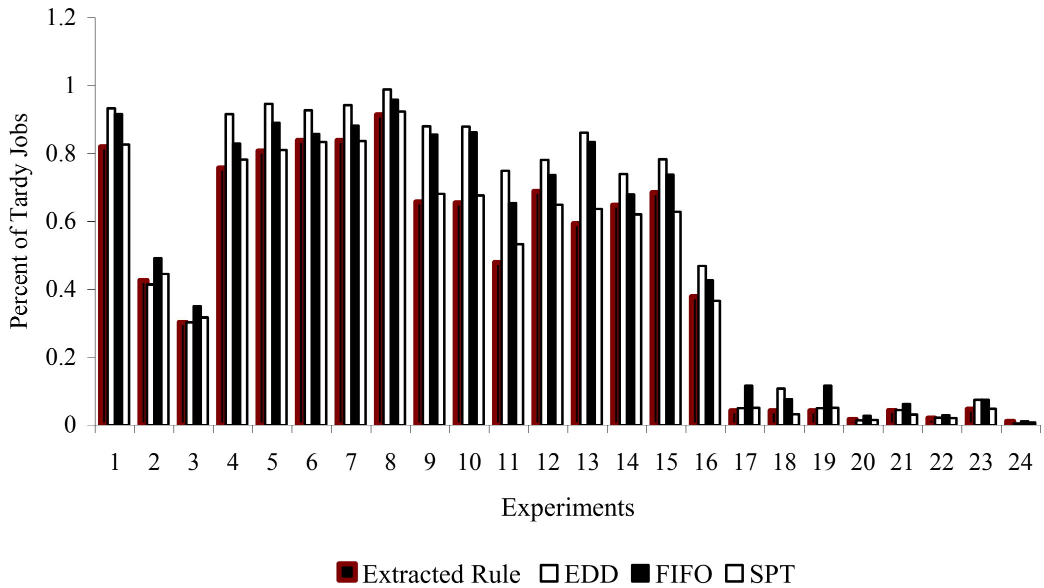


Figure 4.6. T (%) results with respect to dispatching rules

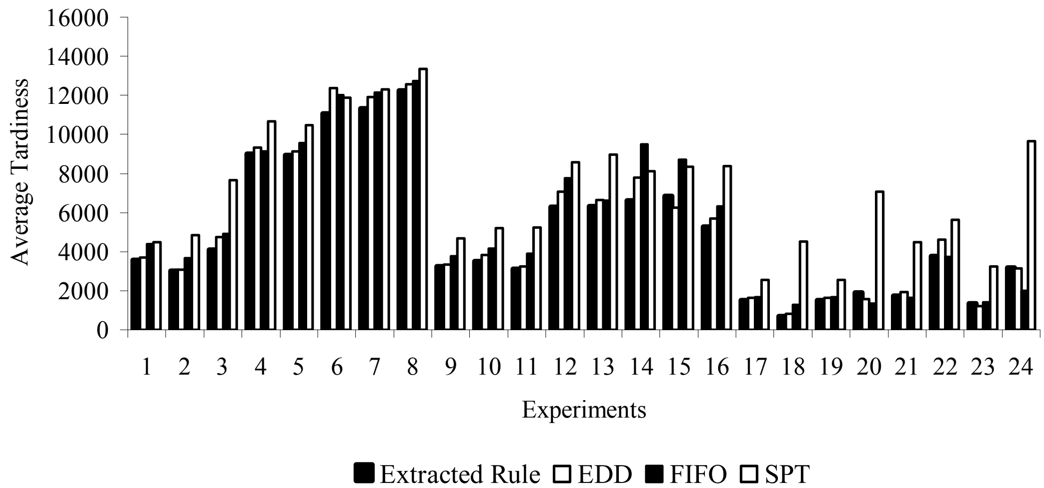


Figure 4.7. T_{avg} results with respect to dispatching rules

7. Conclusions

The state of the system frequently changes in job shops due to the dynamic nature of these environments. These frequent changes significantly affects the performances of the conventional DRs due to the fact that their performances are highly problem dependent. Thus, most of the time they can not react to changing levels of the system state which results in poor performance of shop floor. In order to improve the performance of the dispatching process in such environments the most suitable conventional dispatching rule must be utilized in accordance with the system state in time. This problem is a challenging task and continues to be a very active research topic.

This study aims at tackling this problem by utilizing simple and easy to implement conventional DRs interchangeably according to the certain system state. By this aim a new data mining tool which is known as MEPAR-miner is utilized to develop composite dispatching rules. Broadly speaking, by using MEPAR-miner algorithm some classification rules which classify different factor levels (i.e., input parameter values) according to the selected conventional dispatching rules are extracted. In this sense, utilization of simple and easy to implement conventional DRs interchangeably according to the certain system state is enabled. In this study, these extracted classification rules which are in fact a composition of conventional DRs are named as composite dispatching rules. The main idea behind developing such composite DRs is to better satisfaction of selected performance measurements by adopting the most suitable conventional DRs according to the current shop condition. As mentioned, by this way the performance of the conventional rules can be improved.

While developing such composite DRs, full factorial experiments are carried out to determine the effect of input parameters on predetermined performance measurements for each selected conventional DR. Then, MEPAR-miner algorithm is applied to full factorial experiments' results for generating classification rules for each performance measurements considered. Afterwards, 24 different input parameter combinations are selected randomly as a representative of different system states. Then, the performances of developed composite DRs and considered conventional DRs are tested with these 24 different input parameter combinations. Comparison of these additional simulation experiments revealed that the developed composite DRs perform comparatively better than conventional DRs under all performance measures for most of the parameter combinations. Moreover, the noticeable characteristic of the developed composite DRs is that their being high-level rules which makes them comprehensible. Thus, they can also be used to support for human understanding. As a result, developing composite DRs are found to be a promising candidate for achieving better system performance in job shops.

CHAPTER 5

CONCLUSIONS AND FURTHER STUDIES

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

5.1. Conclusions

The results confirm previous research in showing that OR release mechanisms that have controlled release structure lead to a reduction in the amount of WIP in each level of DF. Moreover, at higher DFs very-well balanced WIP levels across work centers can only be achieved by these mechanisms. This suggests that the impact of controlled release is felt more by the availability of flexible capacity.

The impact of controlled release on all other type of shop performances is influenced by the type of DR used. The relative rankings of DRs are not affected by the type of OR mechanism in terms of nearly all performance measurements. But, it is noticeable that the magnitude of the differences is reduced by controlled release. Thus, it can be concluded that controlled release has no impact on the relative rankings of the dispatching rules. However, as Baker (1984a) noted controlled release mechanism interact with simpler DRs and preempts the rule to create a hybrid sequencing rule that compensates for some of the shortcomings of the pure rule. This can be clearly seen in the difference in MAPE performances among FIFO, EDD, and SPT DRs (see Table 3.5). With uncontrolled release (i.e., IMR) the difference in MAPE performance between FIFO and EDD is 20% (i.e., 44-24) and between EDD and SPT is 336 % (i.e., 380-44). But, with controlled release (i.e., WCWT) the difference in MAPE performance between FIFO and EDD is 19% (i.e., 41-22) and between EDD and SPT is 83% (i.e., 124-41).

The acceptance/rejection decision point and OR mechanisms were found to complement each other. It is apparent from the results that acceptance/rejection decisions affect the MLT whereas OR mechanisms significantly affect WIP levels. This conclusion is line up with the previous researches that highlight the importance of the coordination between customer enquiry and job release levels.

AGGWNQ and WCWT OR mechanisms found to be indeed an effective SFC tool especially in controlling MLTs, SFTTs, AQWTs. Also, at all DF these OR mechanisms' T (%) performance is better than that of IMR OR mechanism. However, the results are mixed in terms of AT performance. No clear inferences about whether the controlled release can improve the AT performance of the shop or not can be drawn from the results. From the AT results, it is apparent that OR mechanism, DF, and PSP size interaction affects AT performance significantly. This can be clearly seen from the AT results at low DF (see Table 3.5). In this case, among the OR mechanisms studied, the IMR mechanism is the best overall performer at low PSP size regardless of DR used. Note that, the magnitude of differences among DR mechanisms with FIFO DR is negligible. But, the difference significantly increases with EDD and SPT DRs. Also, note that the relative rankings of OR mechanisms other than IMR significantly depends on DRs. This can be attributed to the sophistication level of controlled release mechanism. However, at intermediate PSP size, the best AT performance is attained with WCWT controlled release mechanism with FIFO DR. In this case, note that the relative rankings of controlled release mechanism changes. Moreover, at high PSP size, the best AT performance is attained with WCWT controlled release mechanism with FIFO and EDD DRs. The IMR with EDD DR is the best overall performer among the OR mechanisms at higher DFs. However, obtaining the best AT performance with IMR and EDD exacted a price in the form of inevitable due date reliability. Thus, it is very difficult to draw clear inferences about AT performances of OR mechanisms under existence of such conflicting performance measurements.

Another interesting result is that as DF increases due date reliability with IMR OR mechanism actually improves whereas due date reliability with AGGWNQ and WCWT only marginally improves when FIFO dispatching rule is used. This suggests that the amount of control exercised makes it impossible to maintain the priorities set at the time of arrival. Thus, it can be concluded that controlled release mechanisms can not enable to assign more reliable due dates than that of uncontrolled release mechanism with FIFO DR at higher DFs. But, it is noticeable that controlled release mechanisms improves the due date reliability with other DRs.

Higher DF essentially works for AGGWNQ and WCWT. Higher DF decreases the possibility of rejecting incoming orders even enables no rejection of orders at higher PSP size. Also, controlled release mechanisms with higher DFs provides shorter makespan (i.e., total completion time of 18000 orders) than that of uncontrolled release mechanism.

From the conclusions above, there are distinct benefits gained from the use of workload concept. MLT, SFTT, AQWT, T (%), and average WIP levels minimized and very well balanced (i.e., for higher DF) across the work centers. However, not all aspects of system performance are necessarily improved (i.e., AT, MAPE). In spite of this fact, the results of this study revealed that controlled release of jobs to the shop floor can substantially improve the performance of the system. Also, simultaneous consideration of complementary relationship among three decision levels strengthens the effectiveness of each decision level and hereby provides additional improvement on shop performance.

5.2. Further Studies

In this thesis, there have found strong evidences in support of the importance of ORR function in SFC even though simple forms of planning smoothing system, controlled release mechanisms and DRs are considered.

In customer enquiry level, only fairly simple acceptance/rejection rule which stands for planning smoothing system is considered. More sophisticated rules and mechanisms may provide even greater improvement in system performance and improve the effectiveness of job release and dispatching level. In job release stage, only fairly simple controlled release mechanisms are considered. Such simpler controlled release mechanisms may discourage to capture the full effect of controlled release. First of all, parameterization of the selected controlled release mechanisms should be optimized according to the measures of shop performance. Other than this, more sophisticated release mechanisms which exercise much more control over the release of jobs to the shop floor should be employed to improve the effectiveness of job release stage. This may improve even the effectiveness of other decision levels. For dispatching level, the same inferences can be drawn. Then, in this stage only naive DRs are used. More sophisticated DRs may provide even greater improvement in system performance. Also, this may improve even the effectiveness of other decision levels. Meanwhile, by doing these, complexity on implementation should be considered while determining the level of sophistication required in each decision level.

REFERENCES

Al-Turki U., Andijani A., and Arifulsalam S. (2004). A new dispatching rule for the stochastic single-machine scheduling problem. *Simulation-Transactions of the Society for Modeling and Simulation International*, **80**, 165-170.

Anderson, E.J., and Nyirenda, J.C. (1990). Two new rules to minimize tardiness in a job shop. *International Journal of Production Research*, **28**, 2277-2292.

Ashby, J.R. and Uzsoy, R. (1995). Scheduling and Order Release in a Single-Stage Production System. *Journal of Manufacturing Systems*, **14**, 290-306.

Baker, K.R. (1984a). The effects of input control in a simple scheduling model. *Journal of Operations Management*, **4,** 99-112.

Baker, K. R. (1984b). Sequencing rules and due-date assignments in a job shop. *Management Science*, **30**, 1093-1104.

Baker, K. R. and Bertrand, J.M.W. (1981). An investigation of due date assignment rules with constrained tightness. *Operation Management*, **1**, 109-120.

Baker, K. R. and Bertrand, J.M.W. (1982). A dynamic priority rule for sequencing against due dates. *Operation Management*, **1**, 37-42.

Baykasoglu, A., Dereli, T., and Göçken, M. (2005). Flow time estimation using data mining, *ICAM'2005 International Conference on Agile Manufacturing*, pp.77-81.

Baykasoğlu, A., Göçken, M., and Özbakır, L. (2007). A Data mining approach to dispatching rule selection in a simulated job shop. *Proceedings of EU/ME 2007 (eds., Geiger, M.J., Habenicht, W.): "Metaheuristics in the Service Industry", 8th Workshop of the EURO Working Group "EU/ME, the European Chapter on Metaheuristics"*, Stuttgart, Germany, pp. 65-71.

Baykasoğlu, A., and Özbakir, L. (2007). MEPAR-miner: Multi-expression programming for classification rule mining. *European Journal of Operational Research*, **183**, 767-784.

Bechte, W. (1988). Theory and practice of load-oriented manufacturing control. *International Journal of Production Research*, **26**, 375-395.

Bertrand, J.W.M. (1983). The use of workload information to control job lateness in controlled and uncontrolled release production systems. *Journal of Operations Management*, **3**, 79-92.

Bertrand, J.W.M. and Van Ooijen, H.P.G. (2002). Workload based order release and productivity: a missing link. *Production Planning & Control*, **13**, 665-678.

Bobrowski, P.M. (1989). Implementing a loading heuristic in a discrete release job shop. *International Journal of Production Research*, **27**, 1935-1948.

Bobrowski, P.M., Park, P.S. (1989). Work strategies in a dual resource constrained job shop. *OMEGA International Journal of Management Science*, **17**, 177-188.

Breipthaupt, J.W., Land, M., and Nyhuis, P. (2002). The workload control concept: theory and practical extensions of load oriented order release. Production Planning & Control, **13**, 625-638.

Browne. J. and Davies. B.J. (1984). The Phased Release of Batches into a Job Shop. *International Joumal of Operations & Production Management,* **4**, 16-27.

Chang, E.C.R. (1997). Heuristics for dynamic job shop scheduling with real-time updated queuing time estimates. *International Journal of Production Research*, **35**, 661-665.

Chang, Y.L., Toshiyuki, S., and Sullivan, R.S. (1996). Ranking dispatching rules by data envelopment analysis in a job shop environment. *IIE Transactions*, **28**, 631–642.

Cheng, T. C. E. (1987). An algorithm for the CON due date determination and sequencing problem. *Computer and Operations Research*, **14**, 537-542.

Cheng, T. C. E. (1988). Simulation study of job shop scheduling with due dates. *International Journal of Systems Science*, **19**, 383-390.

Cheng, T.C.E. and Jiang, J. (1998). Job shop scheduling for missed due date performance. *Computes & Industrial Engineering*, **34**, 297-307.

Chiang, T.C. and Fu, L.C. (2007). Using dispatching rules for job shop scheduling with due date-based objectives. *International Journal of Production Research*, **45**, 3245–3262.

Chiu, C., Chang, P.C., and Chiu, N.H. (2003). A case-based expert support system for due date assignment in a wafer fabrication factory. *Journal of Intelligent Manufacturing*, 14, 287-29.

Conway, Y. R. W. (1965). Prioirty dispatching and work in process inventory on a job shop. *Journal of Industrial Engineering*, **16**, 123-130.

Conway, R.W., Maxwell, W.L., and Miller, L.W. (1967). *Theory of Scheduling*. Massachusetts: Addison Wesley.

Dessouky, M.M. and Leachman, R.C. (1994). An optimization-based methodology for release scheduling. *Production and Operations Management*, **3**, 276-295.

Eilon, S. and Chowdhury, I.G. (1976). Due-dates in job shop scheduling. *International Journal of Production Research*, **14**, 223-237.

Eilon, S., Chowdhury, I.G., and Serghiou, S.S. (1975). Experiments with SI* rule in job shop scheduling. *Simulation*, **24**, 45-48.

El-Bouri, A. and Shah, P. (2006). A neural network for dispatching rule selection in a job shop. *International Journal of Advanced Manufacturing Technology*, **31**, 342–349.

Enns, S.T. (1993). Job shop flowtime prediction and tardiness control using queuing analysis. *International Journal of Production Research*, **31**, 2045-2057.

Enns, S.T. (1995). A dynamic forecasting model for job shop flowtime prediction and tardiness. *International Journal of Production Research*, **33**, 1295-1312.

Enns, T.S. (2000). Evaluating shop-floor input control using rapid modeling. *International Journal of Production Economics*, **63**, 229-241.

Enns, S.T. and M.P. Costa (2002). The effectiveness of input control based on aggregate versus bottleneck work loads, *Production Planning & Control*, **13**, 614-624.

Gee, E.S. and Smith, H. (1993). Selecting allowance policies for improved job shop performance. *International Journal of Production Research*, **31**, 1839-1852.

Garey, M.R., Johnson, D.S., and Sethi, R. (1976). The complexity of flowshop and jobshop scheduling. *Mathematics of Operations Research*, **1**, 117–129.

Giannelos, N., Papakostas, N., Mourtzis, D., and Chryssolouris, G. (2007). Dispatching policy for manufacturing jobs and time-delay plots. *International Journal of Computer Integrated Manufacturing*, **20**, 329–337.

Glassey, C.R., and Resende, M.C. (1988). Closed-loop job release control for VLSI circuit manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, **1**, 36-48.

Graves, S.C., 1986. A tactical planning model for a job shop, *Operations Research*, **34**, 522-533.

Harty, J.D. (1969). Controlling production capacity. *American production and Inventory Control Society 12th Annual Conference Proceedings*, pp. 60-64.

Hendry, L. and Kingsman B. (1991). Production planning systems and their applicability to make-to-order companies. *European Journal of Operational Research*, **40**, 1-15.

Hendry, L. and Kingsman B. (1991). A Decision Support System for Job Release in Make-to-order Companies. *International Journal of Operations & Production Management*, **11**, 6-16.

Hendry, L. and Kingsman B., 1991. Job Release: Part of a hierarchical system to manage manufacturing lead times in make-to-order companies. *The journal of Operational Research Society*, **42**, 871-883.

Hendry, L.C., Kingsman, B.G., and Cheung, P. (1998). The effect of workload control (WLC) on performance in make-to-order companies. *Journal of Operations Management*, **19**, 63-75.

Hendry, L.C. and Wong, S.K. (1994). Alternative order release mechanisms: a comparison by simulation. *International Journal Production Research*, **32**, 2827-2842.

Hill, T. (1991). *Production/Operation Management, Text and Cases*. New York: Prentice Hall.

Hino, C.M., Ronconi, C.P., and Mendes, A.B. (2005). Minimizing earliness and tardiness penalties in a single-machine problem with a common due date. *European Journal of Operational Research*, **160**, 190-201.

Holthaus, O. and Rajendran C. (1997). New dispatching rules for scheduling in a job shop–An experimental study. *International Journal of Advanced Manufacturing Technology*, **13**, 148–153.

Hopp, W. and Spearman, M.L., (1996). *Factory Physics.* Chigaco: Irwin.

ten Kate, H.A. (1994). Towards a better understanding of order acceptance. *International Journal Production Economics*, **37**, 139-152.

Holthaus O. and Rajendran C. (1997). New dispatching rules for scheduling in a job shop–An experimental study. *The International Journal of Advanced Manufacturing Technology*, **13**,148–153.

Imtiaz, A. and Fisher, W.W. (1992). Due date assignment, job order release, and sequencing interaction in job shop scheduling. *Decision Sciences***, 23**, 633-647.

Jones, A. and Rabelo, L.C. (2007): Survey of job shop scheduling techniques. *National Institute of Standards and Technology Manufacturing Engineering Laboratory Publications. Available online at: http://ws680.nist.gov/mel/div820/pubstracking/search.asp (accessed September 2007).*

Irastorza, J.C. and Deane, R.H. (1974). A loading balancing methodology for job shop control. *AIEE Transactions*, **6**, 302-307.

Kingsman, B. (2000). Modelling input-output workload control for dynamic capacity planning in production planning systems. *International Journal of Production Economics*, **68**, 73-93.

Kingsman, B.G., Tatsiopoulus, I.P., and Hendry, L.C. (1989). A structural methodology for managing manufacturing lead times in make-to-order companies. *European Journal of Operational Research*, **40**, 196-209.

Kiran, A.S. and Smith, M.L. (1984). Simulation studies in job shop scheduling-II: performance of priority rules. *Computers & Industrial Engineering*, **8**, 95–105.

Land, M. and Gaalman, G. (1996). Workload control concepts in job shops: A critcal assessment. *International Journal of Production Economics*, **46-47**, 535-548.

Law A. M., Kelton W.D. (2000). *Simulation modeling and analysis*. Singapore: McGraw-Hill.

Li, X. and Olafsson, S. (2005). Discovering dispatching rules using data mining. *Journal of Scheduling*, **8**, 515–527.

Lingayat, S., Mittenthal, J., and O'Keefe, M. (1995). An order release mechanism for a flexible flow system. *International Journal of Production Research*, **33**, 1241-1256.

Mather, H. and Plossl, G. (1978). Priority fixation versus throughput planning. *Production and Inventory Managemen*, **19**, 27-51.

Melnyk, S.A., Carter, P.L., Dilts, D.M., and Lyth, D.M. (1985). Shop Floor Control, Homewood, IL: Dow Jones-Irwin.

Melnyk, S.A., and Ragatz G.L. (1988). Order Review/Release and its impact on the shop floor. *Production and Inventory Management Journal*, **29**, 13-17.

Melnyk, S.A. and Ragatz, G.L. (1989). Order review\release: Research issues and perspectives. *International Journal of Production Research*, **27**, 1081-1096.

Melnyk, S.A., Ragatz, G.L., and Fredendall, L. (1991). Load Smoothing by the Planning and Order Review/Release Systems: A Simulation Experiment. *Journal of Operations Management*, **10**, 512-523.

Melnyk, S.A., Denzler, D. R., Magnan, G. L., and Fredendall, L. (1994). An experimental model for investigating the sensitivity of job shop performance to job release time distribution parameters. *Production and Operations Management*, **3**, 64-74.

Melnyk, S.A., Tan, K.C., Denzler, D.R., and Fredendall, L. (1994). Evaluating variance control, order review\release and dispatching: a regression analysis. *International Journal of Production Research,* **32**, 1045-1061.

Melnyk, S.A., Vickery S.K., and Carier, P.L. (1986). Scheduling, sequencing, and dispatching: alternative perspectives. *Production and Inventory Management Journal*, **27**, 58-68.

Miyazaki, S. (1981). Combined scheduling system for reducing job tardiness in a job shop. *International Journal of Production Research*, **19**, 201-211.

Moses, S., Grant, H., Gruenwald, L., and Pulat, S. (2004). Real-time due-date promising by build to order environments. *International Journal of Production Research,* **42**, 4353-4375.

Muth, J.F., and Thompson, G.L. (1963). *Industrial scheduling*. New Jersey: Prentice-Hall.

Nandi, A. and Rogers, P. (2003). Behavior of an order release mechanism in a make-to-order manufacturing system with selected order acceptance. *Proceeding of the 2003 Winter Simulation Conference*, pp. 1251-1259.

Nandi, A. and Rogers, P. (2004). Using simulation to make-to-order acceptance/rejection decision, *Simulation*, **80**, 131-142.

Nicholson, T.A.J. and Pullen, R.D. (1972). A practical control system for optimizing production schedules. *International Journal of Production Research*. **16**, 219-227.

Onur L. and Fabrycky, W.J. (1987). An input/output control system for the dynamic job shop. IIE Transactions, **19**, 88-97.

Pierreval, H. and Mebarki, N. (1997). Dynamic selection of dispatching rules for manufacturing system scheduling. *International Journal of Production Research*, **35**, 1575–1591.

Philipoom, P. R. (2000). The choice of dispatching rules in a shop using internally set due dates with quoted lead time and tardiness costs. *International Journal of Production Research*, **38**, 1641-1655.

Philipoom, P.R. and Fry, T.D. (1992). Capacity-based order review/release strategies to improve manufacturing performance. *International Journal of Production Research*, **30**, 2559-2572.

Philipoom, P.R., Rees, L.P., Wiegmann, L. (1994). Using neural networks to determine internally-set due-date assignments for shop scheduling. *Decision Sciences*, **25**, 825-851.

Plossl, G.W. (1985). *Production and inventory control*. (2nd ed.). New Jersey: Prentice Hall.

Raaymakers, W.M., Bertrand, J.W., and Fransoo J.F. (2000a). The performance of workload rules for order acceptance in batch chemical manufacturing, *Journal of Intelligent Manufacturing*, **11**, 217-228.

Raaymakers, W.M., Bertrand, J.W., and Fransoo J.F. (2000b). Using aggregate estimation models for order acceptance in a decentralized production control structure for batch chemical manufacturing, *IIE Transactions*, **32**, 989-998.

Ragartz, G.L. and Mabert, V.A. (1984a). A simulation analysis of due date assignment rules. *Journal of Operation Management*, **5**, 27-39.

Ragartz, G.L. and Mabert, V.A. (1984b). Framework for the study of due date management in job shop. *International Journal of Production Research*, **22**, 685-695.

Ragatz, G.L. and Mabert, V.A. (1988). An evaluation of order release mechanisms in a job-shop environment. *Decision Sciences*, **19**, 167-189.

Raghu, T.S. and Rajendran, C. (1995). Due-date setting methodologies based on simulated annealing- an experimental study in a real-life job shop. *International Journal of Production Research*, **33**, 2535-2554.

Roderick, L.M., Phillips, D.T., and Hogg, G.L. (1992). A comparison of order release strategies in production control systems. *International Journal of Production Research*, **30**, 611-626.

Sabuncuoglu, İ. and Comlekci, A. (2002). Operation based flow time estimation in a dynamic shop. *Omega*, **30**, 423-442.

Sabuncuoğlu, İ. and Karapınar, H.Y. (1999). Analysis of order review/release problems in production systems. *International Journal of Production Economics*, **62**, 259-279.

Sha, D.Y. and Liu, C.H. (2004). Using data mining for due date assignment in a dynamic job shop environment. *International Journal of Advanced Manufacturing Technology*, **25**, 1164-1174.

Shaw, M.J., Park, S., and Raman, N. (1992). Intelligent scheduling with machine learning capabilities: The induction of scheduling knowledge, *IIE Transactions*, **24**, 156– 168,

Shimoyashiro, S., Isoda, K., and Awane, H. (1984). Input Scheduling and Load Balance Control for a Job Shop. *Intemational Joumal of Production Research,* **22**, 597-605.

Smith, M.L. and Seidman, A. (1983). Due date selection procedures for job-shop simulation. *Computers & Industrial Engineering*, **7**, 199-207.

Spearman, M.L., Woodruff, D.L., and Hopp, W.J., (1990). CONWIP: a pull alternative to kanban. *International Journal of Production Research*, **28**, 879-894.

Stevenson, M. and Hendry L. 2006. Aggregate load-oriented workload control: A review and a re-classification of a key approach. *International Journal of Production Economics*, **104**, 676-693.

Subramaniam, V., Ramesh, T., Lee, G.K., Wong, Y.S., and Hong, G.S. (2000). Job shop scheduling with dynamic fuzzy selection of dispatching rules. *International Journal of Advanced Manufacturing Technology*, **16**, 759–764.

Tatsiopoulos, I.P. and Kingsman, B.G. (1983). Lead time management. *European Journal of Operational Research*, **13**, 351-358.

Tsai, C. –H., Chang, G. –T., and LI, R. –K. (1997). Integrating order release control with due-date assignment rules. *International Journal of Production Research*, **35**, 3379-3392.

Veral, E.A. (2001). Computer simulation of due-date setting in multi-machine job shops. *Computes & Industrial Engineering*, **41**, 77-94.

Vig, M.M. and Dooley, K.J. (1991). Dynamic rules for due date assignment. *International Journal of Production Research*, **29**, 1361-1377.

Waikar, A. Sarker, B., and Lal, A. (1995). A comparative study of some priority dispatching rules under different shop loads. *Produciton Plannning & Control*, **6**, 301–310, Wang, J., Yang, J.Q., and Lee. H. (1994). Multicriteria order acceptance decision support in over demanded job-shops: A neural network approach. *Mathematical and Computer Modelling*, **19**, 1-19.

Wang, K.J., Chen, J.C., and Lin, Y.S. (2005). A hybrid knowledge discovery model using decision tree and neural network for selecting dispatching rules of a semiconductor final testing factory. *Production Planning & Control*, **16**, 665–680.

Weeks, J.K. and Fryer, J.S., (1977). A methodology for assigning mininum cost due-dates. *Management Science*, **25**, 363-373.

Wester, F. W., Wijngaard, J., and Zijm, W. M. (1992). Order acceptance strategies in a production-to-order environment with setup times and due-dates, *International Journal Production Research*, **30**, 1313-1326.

Wight, O. (1970). Input/Output control: A real handle on lead time. *Production and Inventory Management*, **3**, 9-31.

Wilson J.H. and Keating, B. (2002). *Business Forecasting*. New York: McGraw-Hill.

Wisner, J.D. (1995). A review of the order release policy research. *International Journal of Operations & Production Management*, **15**, 25-40.

Wouters, M. J. (1997). Relevant cost information for order acceptance decisions. *Production Planning & Control*, **8**, 2-9.

Zapfel, G. and Missbauer, H. (1993). New concepts for production planning and control. *European Journal of Operational Research*, **67**, 297-320.

APPENDIX A

SETTING APPROPRIATE WLLs FOR OR MECHANISMS

This appendix provides graphical illustrations of MAPE, MLT, SFTT, AT, AQWT, T (%), M, R, and WIP performances with different levels of WLL of AGGWNQ and WCWT OR mechanisms at all other factor level combinations with respect to each DF, separately.

A.1. Setting appropriate WLL with AGGWNQ OR mechanism

The WIP levels with AGGWNQ OR mechanism for each work center are given in Tables A.1-A.7. Note that, in Table A.1 results are obtained at low degree of flexibility. This means, in such a system, an operation of an order has no alternative machine to be processed. From Table A.1, it is noticeable that for all levels of DR, and PSP size the low level of WL (i.e., 500) minimizes average WIP levels for each work center over time. Another noticeable result is that there exists a linear relationship between average WIP levels of bottleneck work centers and predetermined WLLs for each level of PSP size. Also, there exists an interaction between PSP size and WLLs. For example, if we set PSP size either 1000 or 3000 approximately the same average WIP levels are obtained for all work centers independent of DRs. But, when we set PSP size as 2000, average WIP levels are increased for WC 1 and WC 2 whereas it is decreased for WC 3 independent of DRs. Note that, DR has no significant effect on average WIP levels which simplifies the second stage experiments. Thus, only one WLL determination will be adequate for all DR. Note that the dispersion of the average WIP levels among the work centers is not balanced. High variability of WIP levels across the work centers is indicated by high variance of WIP value which is given in the last column. As a result WC 1, WC 2, and WC 3 are all become bottleneck stations when the degree of flexibility is 0. *Consequently, the appropriate WLL with AGGWNQ OR mechanism should be 500 at low degree of flexibility.*

Table A.1. Average WIP levels with AGGWNQ at low DF

Factors and their levels					Work centers										
DF	OR Mec.	DR	PSP Size	WLL	1	2	3	4	5	6	7	8	9	10	Var of
1	AGGWNQ	FIFO	1000	500	13	0	57	1	0	1	12	1	0	1	314
			1000	1000	27	0	117	1	0	1	25	1	0	1	1339
			1000	1500	39	0	180	1	0	2	38	1	0	1	3168
			2000	500	21	0	42	1	0	2	21	2	0	1	205
			2000	1000	41	1	91	1	0	2	41	2	1	1	931
			2000	1500	59	1	145	1	0	2	59	2	1	1	2295
			3000	500	16	0	50	1	0	2	16	2	1	1	248
			3000	1000	32	1	106	1	0	2	32	3	1	1	1122
			3000	1500	39	1	177	1	0	2	40	2	1	1	3055
		EDD	1000	500	13	0	55	1	0	1	15	1	0	1	296
			1000	1000	26	0	119	1	0	1	25	1	0	1	1382
			1000	1500	41	0	179	1	0	2	37	2	0	1	3132
			2000	500	20	0	43	1	0	2	21	2	0	1	210
			2000	1000	43	1	88	1	0	2	42	2	1	1	899
			2000	1500	63	1	138	1	0	2	62	2	1	1	2169
			3000	500	16	1	50	1	0	2	16	2	1	1	246
			3000	1000	32	1	106	1	0	2	32	3	1	1	1122
			3000	1500	43	1	170	1	0	3	43	2	1	1	2844
		SPT	1000	500	13	0	58	1	0	1	13	1	0	1	326
			1000	1000	21	0	121	1	0	1	29	1	0	1	1429
			1000	1500	42	0	176	1	0	1	42	1	0	1	3060
			2000	500	20	0	46	1	0	1	20	1	0	1	234
			2000	1000	39	0	95	1	0	1	39	1	0	1	993
			2000	1500	59	0	143	1	0	2	62	2	0	1	2277
			3000	500	15	0	53	1	0	1	15	1	0	1	278
			3000	1000	27	0	114	1	0	2	28	2	0	1	1273
			3000	1500	37	0	181	1	0	2	38	2	0	1	3191

The resulting WIP levels for each work center which are obtained at intermediate degree of flexibility with AGGWNQ OR mechanism are shown in Table A.2. This means, in such a system, an operation of an order have two alternative machines to be processed at one of them. From Table A.6., for all levels of DR, and PSP size minimum WLL (i.e., 500) minimizes average WIP levels for each work center over time. Another important result is that the average WIP level of each work center is only affected by the levels of WLL. Note that, the resulting average WIP level for each work center is proportional to WLL levels. Another important result is that the PSP Size factor has no significant effect on the average WIP performance. Thus, contrary to Table A.1 results, no interaction between PSP size and WLLs is observed when the degree of flexibility is 1. From Table A.2, it is apparent that average WIP levels are insensitive to DRs used which simplifies the second stage experiments. Thus, only one WLL determination will be adequate for all DR and also for all PSP size. Note that the dispersion of the average WIP levels across the work centers is balanced. So, we can say that the degree of flexibility is much more important so as to smooth out peaks and valleys of the average WIP levels among the work centers. Note that, much more lower variance of WIP values are attained at intermediate degree of flexibility. It also helps to diminish the effect of PSP size on the WIP levels. *Consequently, the appropriate WLL with AGGWNQ OR mechanism should be 500 at intermediate degree of flexibility.*

Table A.2. Average WIP levels with AGGWNQ at intermediate DF

Factors and their levels					Work centers										
DF	OR Mec.	DR	PSP Size	WLL	1	2	3	4	5	6	7	8	9	10	Var of WIP
2	AGGWNQ	FIFO	1000	500	11	13	12	10	13	12	10	11	12	13	1.3
			1000	1000	23	26	24	20	28	26	22	22	26	27	6.7
			1000	1500	34	39	35	30	43	40	32	33	39	41	18.9
			2000	500	11	13	12	10	13	12	11	11	12	13	1.1
			2000	1000	23	26	23	20	28	26	22	22	26	28	7.6
			2000	1500	34	39	35	30	43	40	32	33	39	41	18.9
			3000	500	11	13	12	10	13	12	11	11	12	13	1.1
			3000	1000	23	26	23	20	28	26	22	22	26	28	7.6
			3000	1500	34	39	35	30	43	40	32	33	39	41	18.9
		EDD	1000	500	11	13	12	10	13	12	10	11	12	13	1.3
			1000	1000	22	26	23	20	28	26	21	22	25	27	7.6
			1000	1500	32	38	34	29	41	38	31	32	37	40	17.1
			2000	500	11	13	12	10	13	12	10	11	12	13	1.3
			2000	1000	22	26	23	20	28	26	21	22	25	27	7.6
			2000	1500	32	38	34	29	41	38	31	32	37	40	17.1
			3000	500	11	13	12	10	13	12	10	11	12	13	1.3
			3000	1000	22	26	23	20	28	26	21	22	25	27	7.6
			3000	1500	32	38	34	29	41	38	31	32	37	40	17.1
		SPT	1000	500	10	11	10	9	12	11	9	9	11	12	1.4
			1000	1000	20	23	21	18	24	22	19	19	22	23	4.1
			1000	1500	30	35	31	28	35	32	28	29	32	34	7.2
			2000	500	10	11	10	9	12	11	9	10	11	12	1.2
			2000	1000	20	22	20	18	24	23	19	20	22	23	3.9
			2000	1500	29	34	31	28	35	33	29	30	33	34	6.3
			3000	500	10	10	10	10	10	10	10	10	10	10	0.0
			3000	1000	20	22	20	18	24	23	19	20	22	23	3.9
			3000	1500	29	34	31	28	35	33	29	30	33	34	6.3

The resulting WIP levels for each work center which are obtained at high degree of flexibility with AGGWNQ OR mechanism are shown in Table A.3. This means, in such a system, an operation of an order have three alternative machines to be processed at one of them. The results of this system are consistent with the results of the system with intermediate degree of flexibility with one difference. In such a system, it is observed that increasing flexibility of the system fine tunes the balance of average WIP across WCs. This can be seen from the variance of average WIP values across WCs in the last column of each Table. Note that if average WIP levels are well balanced this value must be about zero. Thus, lower values of variance of average WIP are desired and in fact are obtained at high degree of flexibility. Looking at the last column of both Table A.3 and Table A.3 one can easily say that by increasing the degree of flexibility we obtain more balanced average WIP levels across work centers. *Consequently, the appropriate WLL with AGGWNQ OR mechanism should be 500 at high degree of flexibility.*

Table A.3. Average WIP levels with AGGWNQ at high DF

Factors and their levels					Work centers										Var of WIP
DF	OR Mec.	DR	PSP Size	WLL	1	2	3	4	5	6	7	8	9	10	
3	AGGWNQ	FIFO	1000	500	12	12	11	12	12	13	12	11	12	13	0.4
			1000	1000	25	25	22	24	24	28	25	22	24	27	3.6
			1000	1500	37	38	32	36	36	42	37	34	36	40	8.0
			2000	500	12	12	11	12	12	13	12	11	12	13	0.4
			2000	1000	25	25	21	24	24	28	25	22	24	27	4.3
			2000	1500	37	38	32	35	36	42	38	34	36	40	8.4
			3000	500	12	12	11	12	12	13	12	11	12	13	0.4
			3000	1000	25	25	21	24	24	28	25	22	24	27	4.3
			3000	1500	37	38	32	35	36	42	38	34	36	40	8.4
		EDD	1000	500	12	12	12	12	12	12	12	12	12	12	0.0
			1000	1000	24	25	21	23	23	27	24	22	23	26	3.3
			1000	1500	35	36	31	34	34	40	36	32	34	38	7.1
			2000	500	12	12	10	11	11	13	12	11	12	13	0.9
			2000	1000	24	25	21	23	23	27	24	22	23	26	3.3
			2000	1500	35	36	31	34	34	40	36	32	34	38	7.1
			3000	500	12	12	10	11	11	13	12	11	12	13	0.9
			3000	1000	24	25	21	23	23	27	24	22	23	26	3.3
			3000	1500	35	36	31	34	34	40	36	32	34	38	7.1
		SPT	1000	500	10	10	9	9	9	11	10	9	10	11	0.6
			1000	1000	20	21	18	19	19	23	20	18	20	22	2.7
			1000	1500	30	31	27	28	29	34	30	27	29	33	5.5
			2000	500	10	10	9	9	9	11	10	9	10	11	0.6
			2000	1000	20	21	18	19	19	23	20	18	20	22	2.7
			2000	1500	30	31	27	28	29	34	30	27	29	33	5.5
			3000	500	10	10	9	9	9	11	10	9	10	11	0.6
			3000	1000	20	21	18	19	19	23	20	18	20	22	2.7
			3000	1500	30	31	27	28	29	34	30	27	29	33	5.5

Consequently, for AGGWNQ OR mechanism, one should set WLL value to 500 to improve average WIP performance of shop regardless of the degree of flexibility. Below, the same analyses are made for WCWT OR mechanisms.

A.2. Setting appropriate WLL with WCWT OR mechanism

The WIP levels with WCWT OR mechanism for each work center are given in Tables A.4-A.6. Note that, in Table A.4 results are obtained at low degree of flexibility. This means, in such a system, an operation of an order has no alternative machine to be processed. From Table A.4, it is noticeable that for all levels of DR, and PSP size the low level of WL (i.e., 500) minimizes average WIP level for each work center over time. WC 1, WC 3, and WC 7 are all become bottleneck work centers. Among them, average WIP level of WC 1 and WC 7 significantly affected by both PSP size and WL but does not significantly affected by DR. However, average WIP level of WC 3 is affected by all factors. Low levels of both PSP size and WL improve average WIP performance of these work centers. But, the results for WC 3 are somewhat complicated. The average WIP performance of WC 3 is affected by all factors and their interactions. Low levels of all factors improve average WIP performance of WC 3 but for higher levels of factors average WIP is affected by main factors and interactions of them. Note that the dispersion of the average WIP across the WCs is not balanced. This is also seen from the variances of WIP values which are given in the last column of Table A.4. Unbalanced average WIP across the WCs is indicated by high values of the variance of WIP. *Consequently, the appropriate WLL with WCWT OR mechanism should be 50 at low degree of flexibility.*

Table A.4. Average WIP levels with WCWT at low DF

DF	OR Mec.	DR	PSP Size	WLL	Work Centers										Var of WIP
					1	2	3	4	5	6	7	8	9	10	
0	WCEDD	FIFO	1000	50	8	0	27	1	0	2	8	2	0	1	70
			1000	100	13	0	38	1	0	2	13	2	0	1	145
			1000	150	17	0	44	1	0	2	18	2	0	1	204
			2000	50	12	1	70	1	0	3	13	3	1	1	459
			2000	100	22	1	100	1	0	3	22	3	1	1	958
			2000	150	31	1	89	1	0	3	33	3	1	1	815
			3000	50	13	1	149	1	0	3	13	3	1	1	2127
			3000	100	23	1	197	1	0	4	23	3	1	1	3716
			3000	150	33	1	164	1	0	3	33	4	1	1	2588
		EDD	1000	50	7	0	24	1	0	2	8	2	0	1	55
			1000	100	13	0	31	1	0	2	13	2	0	1	101
			1000	150	18	0	38	1	0	2	18	2	0	1	162
			2000	50	12	1	74	1	0	2	12	2	1	1	517
			2000	100	22	1	66	1	0	3	22	3	1	1	434
			2000	150	32	1	67	1	0	3	32	3	1	1	508
			3000	50	12	1	136	1	0	3	13	3	1	1	1767
			3000	100	23	1	119	1	0	3	23	4	1	1	1350
			3000	150	33	1	113	1	0	4	33	3	1	1	1263
		SPT	1000	50	7	0	21	1	0	1	7	1	0	1	43
			1000	100	12	0	30	1	0	2	12	1	0	1	94
			1000	150	15	0	39	1	0	1	15	1	0	1	160
			2000	50	12	0	56	1	0	2	12	2	0	1	299
			2000	100	21	0	59	1	0	2	22	2	0	1	361
			2000	150	31	0	73	1	0	2	32	2	0	1	590
			3000	50	12	1	105	1	0	2	12	3	1	1	1047
			3000	100	22	1	101	1	0	2	23	2	1	1	984
			3000	150	32	1	128	1	0	2	32	3	1	1	1601

The resulting WIP levels for each work center which are obtained at intermediate degree of flexibility with WCWT OR mechanism are shown in Table A.5. From Table A.5, at each level of DR, and PSP size the low level of WLL minimizes average WIP levels for each work center over time. Another important result is that the average WIP performance of each work center is only affected by the levels of WLL. Note that, average WIP value of each work center is proportional to the levels of WLL. Additionally, note that the dispersion of the average WIP levels across the work centers is well balanced for low level of WL. So, one can say that the level of WL is much more important so as to smooth out peaks and valleys of the average WIP levels among the work centers. *Consequently, the appropriate WLL with WCWT OR mechanism should be 50 at intermediate degree of flexibility.*

Table A.5. Average WIP levels with WCWT at intermediate DF

DF	OR Mec.	DR	PSP Size	WLL	Work Centers										Var of WIP
					1	2	3	4	5	6	7	8	9	10	
1	WCEDD	FIFO	1000	50	13	15	14	12	16	15	12	13	15	15	2
			1000	100	25	29	26	22	31	29	23	24	28	30	10
			1000	150	36	42	37	32	45	42	34	35	41	44	21
			2000	50	13	15	14	12	16	15	13	13	15	16	2
			2000	100	25	29	26	22	32	29	24	24	29	31	11
			2000	150	36	42	37	32	46	43	35	35	41	44	22
			3000	50	13	15	14	12	16	15	13	13	15	16	2
			3000	100	25	29	26	22	32	29	24	24	29	31	11
			3000	150	36	42	37	32	46	43	35	35	41	44	22
		EDD	1000	50	13	15	14	12	16	15	12	12	14	15	2
			1000	100	24	28	25	21	30	28	22	23	27	29	10
			1000	150	33	39	35	30	42	39	32	32	38	41	18
			2000	50	13	15	14	12	16	15	12	12	14	15	2
			2000	100	24	28	25	21	30	28	23	23	27	29	9
			2000	150	33	39	35	30	42	39	32	32	38	41	18
			3000	50	13	15	14	12	16	15	12	12	14	15	2
			3000	100	24	28	25	21	30	28	23	23	27	29	9
			3000	150	33	39	35	30	42	39	32	32	38	41	18
		SPT	1000	50	10	12	11	9	13	12	10	10	12	12	2
			1000	100	20	24	21	19	25	23	20	20	23	24	5
			1000	150	30	35	31	28	35	33	29	30	33	35	7
			2000	50	11	12	11	10	14	12	10	10	12	13	2
			2000	100	21	24	22	20	27	25	21	21	24	25	5
			2000	150	31	36	32	29	37	34	30	31	34	36	8
			3000	50	11	12	11	10	14	12	10	10	12	13	2
			3000	100	21	24	22	20	27	25	21	21	24	25	5
			3000	150	31	36	32	29	37	34	30	31	34	36	8

The resulting WIP levels for each work center which are obtained at high degree of flexibility with WCWT OR mechanism are shown in Table A.6. From Table A.6, for each level of DR, and PSP size the low level of WLL minimizes average WIP for each work center. Another important result is that the average WIP performance of each work center is affected by WL and DR. Also, the average WIP level of each work center changes proportionally as the WL changes. Note that the dispersion of the average WIP across the WCs is well balanced at low WLL. So, we can say that the level of WLL is much more important to smooth out peaks and valleys of the average WIP across the work centers. *Consequently, the appropriate WLL with WCWT OR mechanism should be 50 at high degree of flexibility.*

Table A.6. Average WIP levels with WCWT at high DF

DF	OR Mec.	DR	PSP Size	WLL	Work Centers										Var of WIP
					1	2	3	4	5	6	7	8	9	10	
2	WCEDD	FIFO	1000	50	15	16	13	15	15	17	16	14	15	17	2
			1000	100	28	29	25	27	28	32	29	26	27	32	5
			1000	150	40	42	36	39	40	46	42	37	39	45	10
			2000	50	15	16	13	15	15	17	16	14	15	17	2
			2000	100	28	29	25	27	28	32	29	26	27	32	5
			2000	150	40	42	35	39	40	46	42	37	39	45	11
			3000	50	15	16	13	15	15	17	16	14	15	17	2
			3000	100	28	29	25	27	28	32	29	26	27	32	5
			3000	150	40	42	35	39	40	46	42	37	39	45	11
		EDD	1000	50	14	15	13	14	14	16	15	13	14	16	1
			1000	100	27	28	23	26	26	30	27	24	26	29	4
			1000	150	38	39	33	36	36	43	38	34	37	41	9
			2000	50	15	15	13	14	14	16	15	13	14	16	1
			2000	100	27	28	23	26	26	30	27	24	26	29	4
			2000	150	38	39	33	36	36	43	38	34	37	41	9
			3000	50	15	15	13	14	14	16	15	13	14	16	1
			3000	100	27	28	23	26	26	30	27	24	26	29	4
			3000	150	38	39	33	36	36	43	38	34	37	41	9
		SPT	1000	50	12	12	10	11	11	13	12	11	11	13	1
			1000	100	24	25	21	23	23	27	24	22	23	26	3
			1000	150	35	36	31	33	33	38	34	31	34	37	6
			2000	50	12	12	10	11	11	14	12	11	12	13	1
			2000	100	24	25	21	23	23	27	24	22	24	26	3
			2000	150	35	36	31	33	33	38	35	31	34	38	6
			3000	50	12	12	10	11	11	14	12	11	12	13	1
			3000	100	24	25	21	23	23	27	24	22	24	26	3
			3000	150	35	36	31	33	33	38	35	31	34	38	6

So far, the effect of the levels of WLL on the average WIP performance of the shop at each level of the degree of flexibility is analyzed in this sub-section. From the above analysis it is concluded that the low level of WL gives the best average WIP performance and well balanced WIP levels across the WCs for both OR mechanisms at all levels of other factors. Now, the effect of this level of WL on other predetermined performance measures will be investigated whether it provides satisfactory results for them or not.

A.3 The effect of the levels of WLL with AGGWNQ on other predetermined performance measures at low DF

In Table A.7, the resulting measures of other shop performances with AGGWNQ OR mechanism at low degree of flexibility is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed. Note that these are selected as the main performance measures.

MAPE: From Figure A.7, it is apparent that the MAPE performance of the shop is significantly affected by the levels of DRs and the levels of WL. Also, interaction of PSP size and EDD DR has significant effect on MAPE performance. For FIFO DR, the levels of WL have no significant effect on MAPE performance of the shop. But, for both EDD and SPT DRs the minimum value of WL provides the best MAPE performance for each PSP size level. So, there is no evidence against setting the level of WL to 500 in terms of MAPE performance measure.

MLT: The levels of all factors have significant effect on the MLT performance. At low level of PSP size for all DRs, changing from low to higher WL, MLT performance of the shop deteriorates significantly. At intermediate PSP size for both FIFO and EDD DR, MLT performance is not significantly affected by different levels of WL. But, at this level of PSP size, higher levels of WL improve MLT performance. At high PSP size, for both SPT and EDD DRs, the MLT performance deteriorates as the level of WL decreases. Note that, in this case the decrease in MLT values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL unacceptable. So, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure.

SFTT: The WLL has significant effect on the SFTT performance of the shop. Neither PSP size not the DR factors has significant effect on the SFTT performance of the shop. From Figure A.3, it is apparently seen that low level of WL gives the best SFTT performance. So there is no evidence against setting the level of WL to 500 in terms of SFTT performance measure.

APWT: The levels of WL have little effect on APWT performance at low level of PSP size. For higher levels of PSP size APWT performance is significantly affected by the levels of WL. APWT performance improves as the level of WL increases for other levels of PSP size for all DRs. But, note that there is a trade-off between APWT performance and SFTT performance of the shop. It means that increasing the levels of WL improves APWT performance but worsens SFTT performance. In this case, the MLT performance which is summation of PWT and SFTT performances must be evaluated. As mentioned above, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure so does APWT performance.

AT: AT performance of the shop is affected by all factor combinations. At low level of PSP size factor, low level of WL improves the AT performance for all DRs. But, at higher levels of PSP size factor, low level of WL deteriorates the AT performance for all DRs except SPT DR with medium level of PSP size factor. But, note that even the maximum amount of difference between AT performances (i.e., for each PSP size, for each DR) due to the levels of WL is not significant. So there is no evidence against setting the level of WL to 500 in terms of AT performance measure.

AQWT: The levels of WL have significant effect on the AQWT performance of the shop. The low level of WL yields the best AQWT performance regardless of factors considered. So there is no evidence against setting the level of WL to 500 in terms of AQWT performance measure.

T (%): The T (%) performance of the shop is not significantly affected by the levels of WL. It is mainly affected by both PSP size and DR factors. So, there is no evidence against setting the level of WL to 500 in terms of T (%) performance measure.

M: Makespan performance of the shop is mainly affected by the levels of PSP size factor. The levels of WL have negligible effect on the M performance of the shop. So, there is no evidence against setting the level of WL to 500 in terms of M performance measure.

R: Total number of rejected orders performance of the shop is mainly affected by the levels of PSP size factor. The levels of WL have negligible effect on R performance of the shop. Not many more orders will be rejected by setting the level of WL as 500. So, there is no evidence against setting the level of WL to 500 in terms of R performance measure.

Consequently, the low level of WL improves and\or at least do not deteriorate considerably the predetermined performance measures of the shop at low degree of the flexibility. In Table A.7 all these results are summarized.

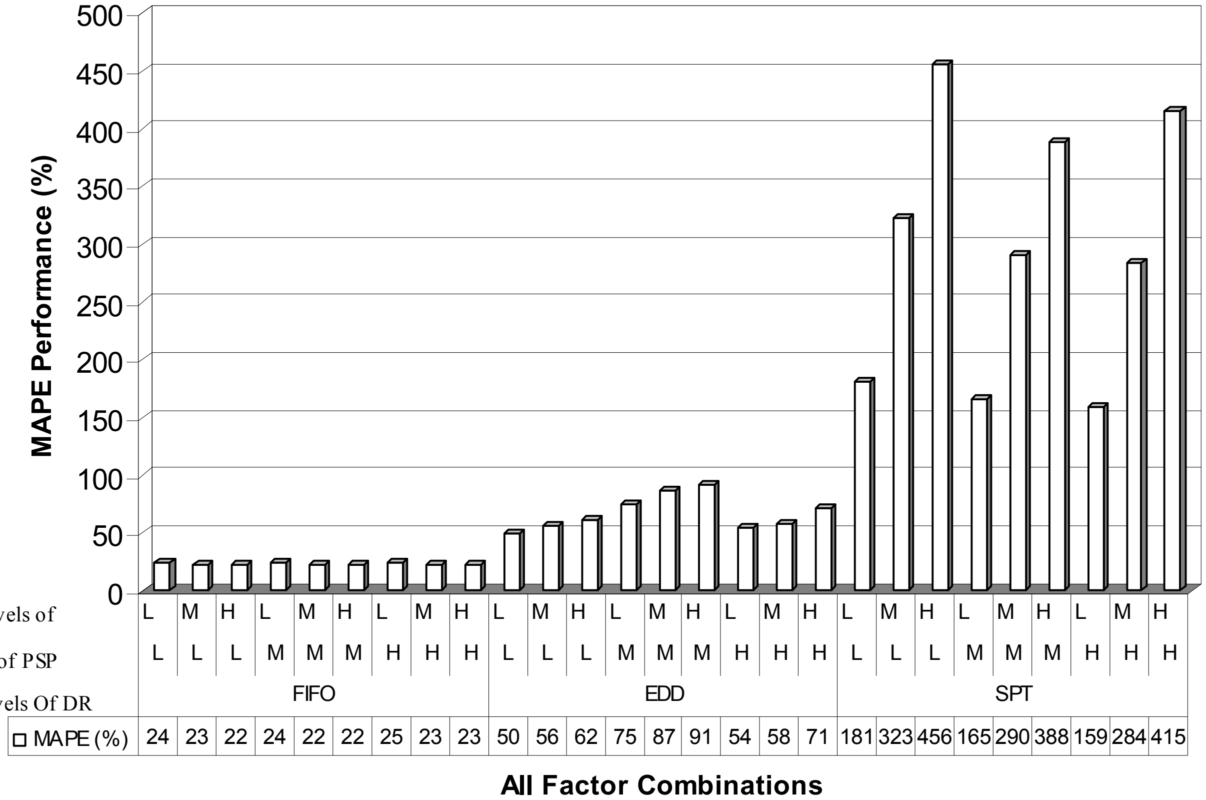
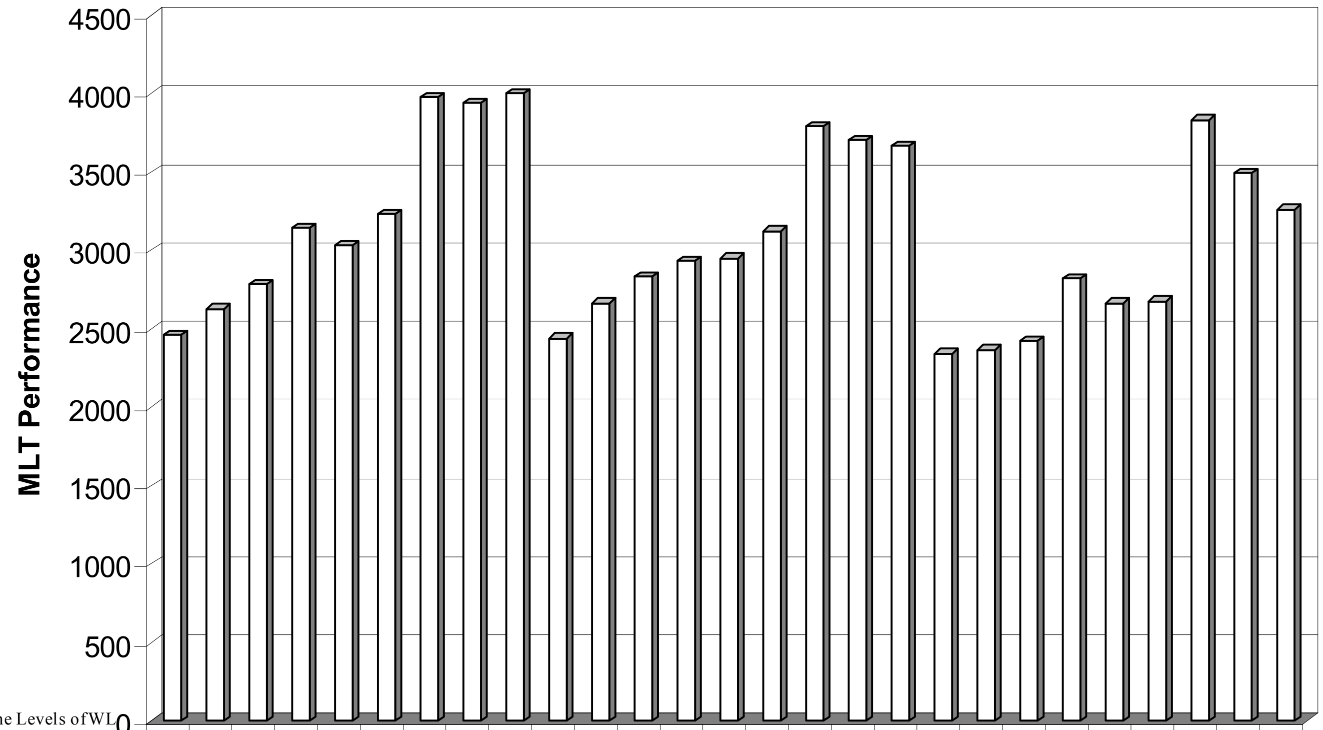
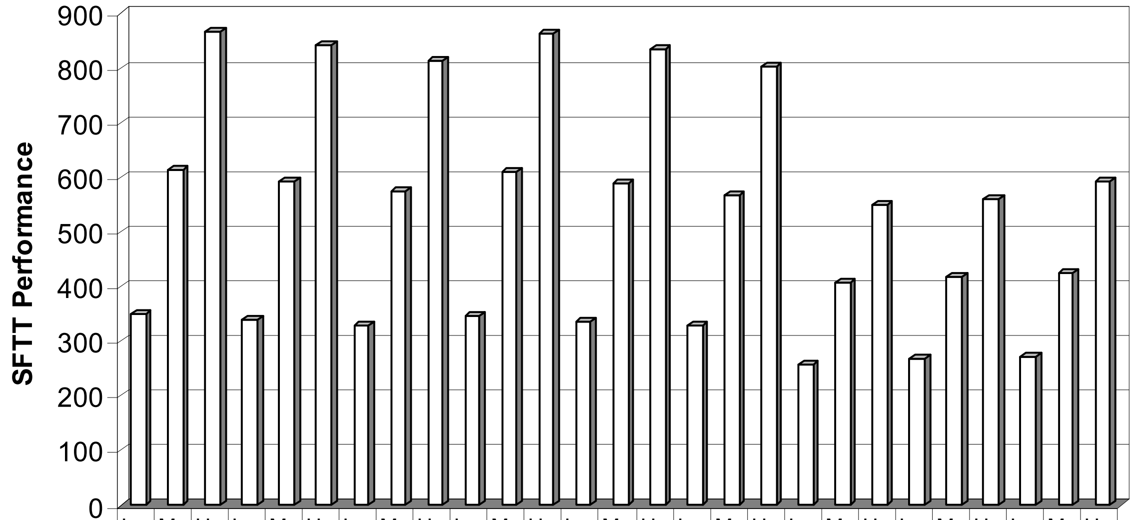


Figure A.1. MAPE Performance with AGGWNQ at low DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The levels of PSP	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
MLT	2465	2630	2785	3145	3029	3230	3974	3936	4001	2441	2665	2832	2929	2950	3126	3792	3702	3667	2343	2368	2423	2819	2667	2677	3832	3494	3263

Figure A.2. MLT Performance with AGGWNQ at low DF



The Levels of	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The levels of PSP	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of	FIFO									EDD									SPT								
SFTT	349	614	867	339	592	844	330	575	815	348	610	863	337	590	835	329	568	805	257	408	550	267	419	559	270	425	594

Figure A.3. SFTT Performance with AGGWNQ at low DF

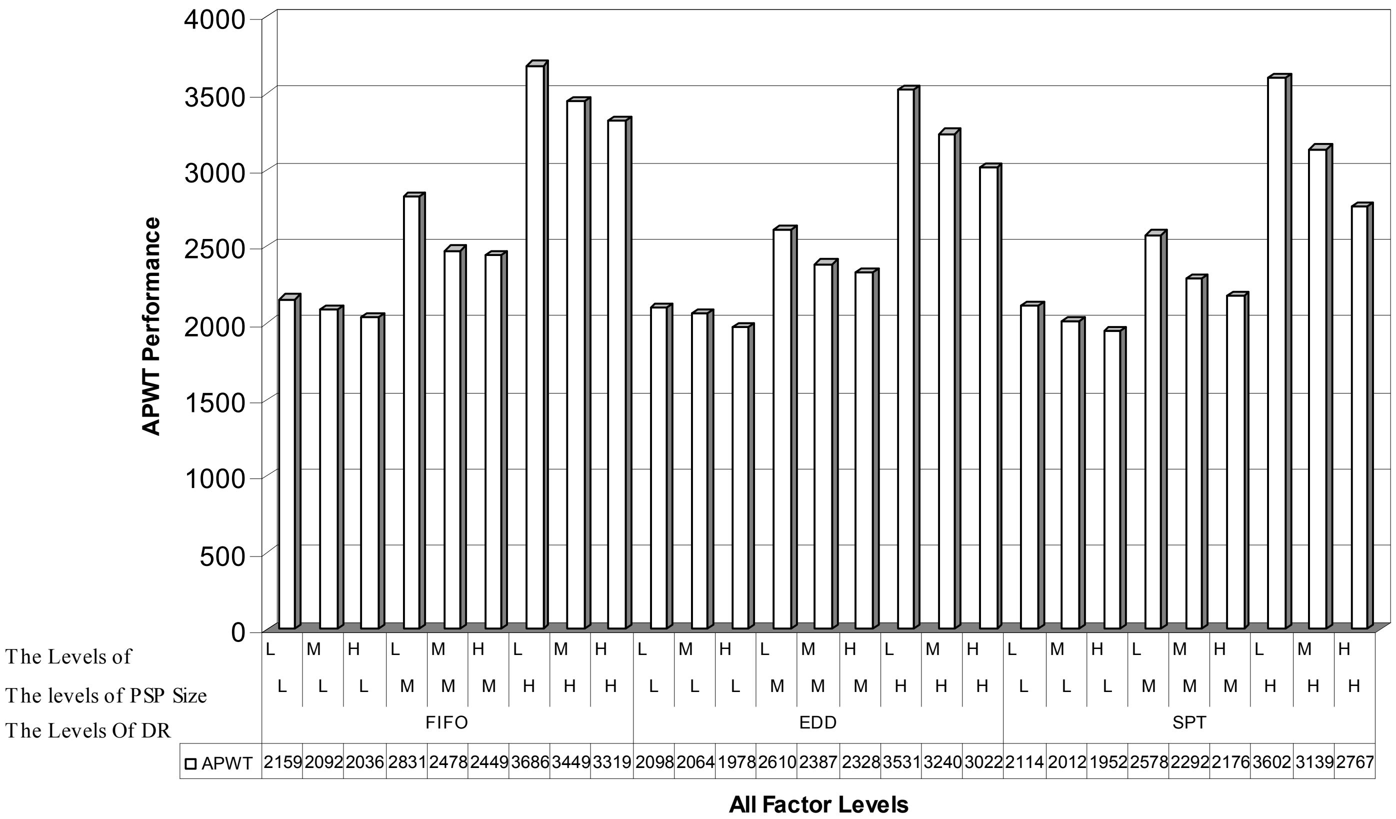


Figure A.4. APWT Performance with AGGWNQ at low DF

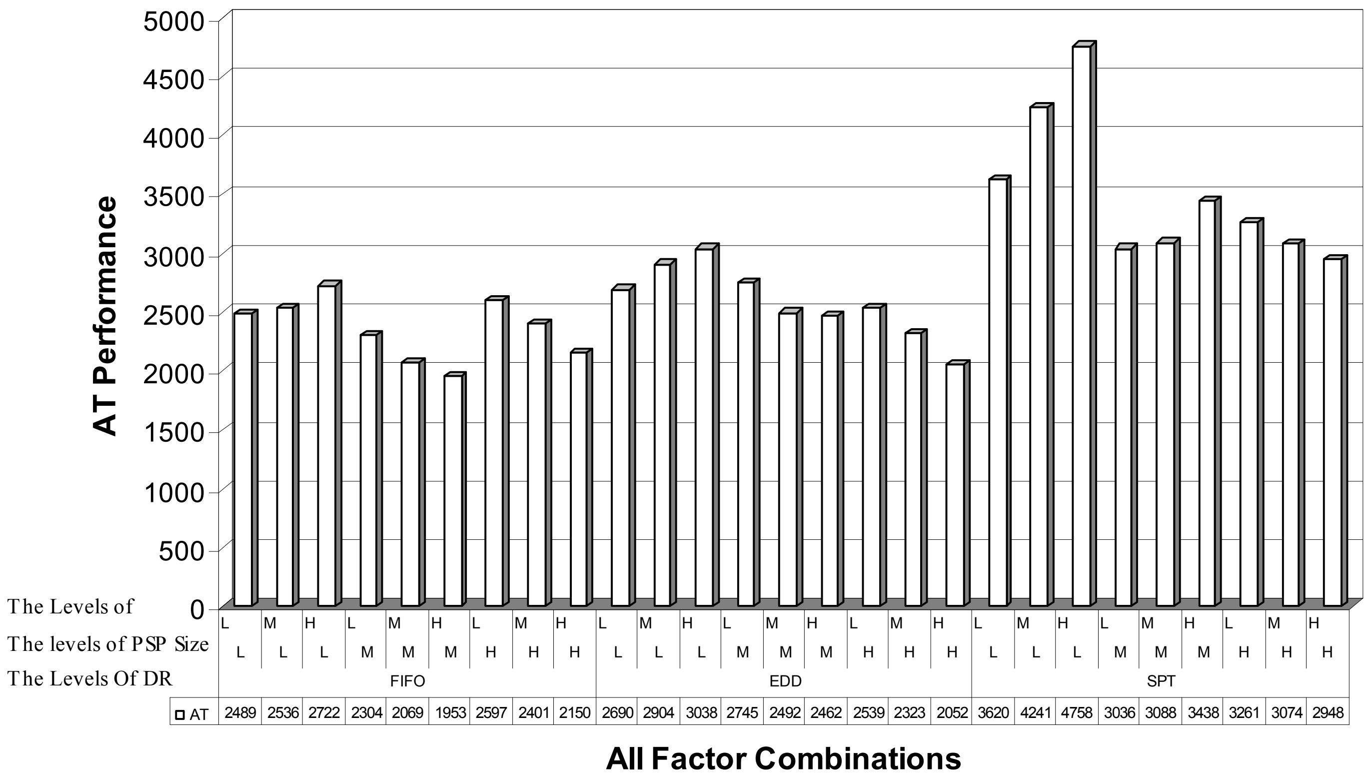


Figure A.5. AT Performance with AGGWNQ at low DF

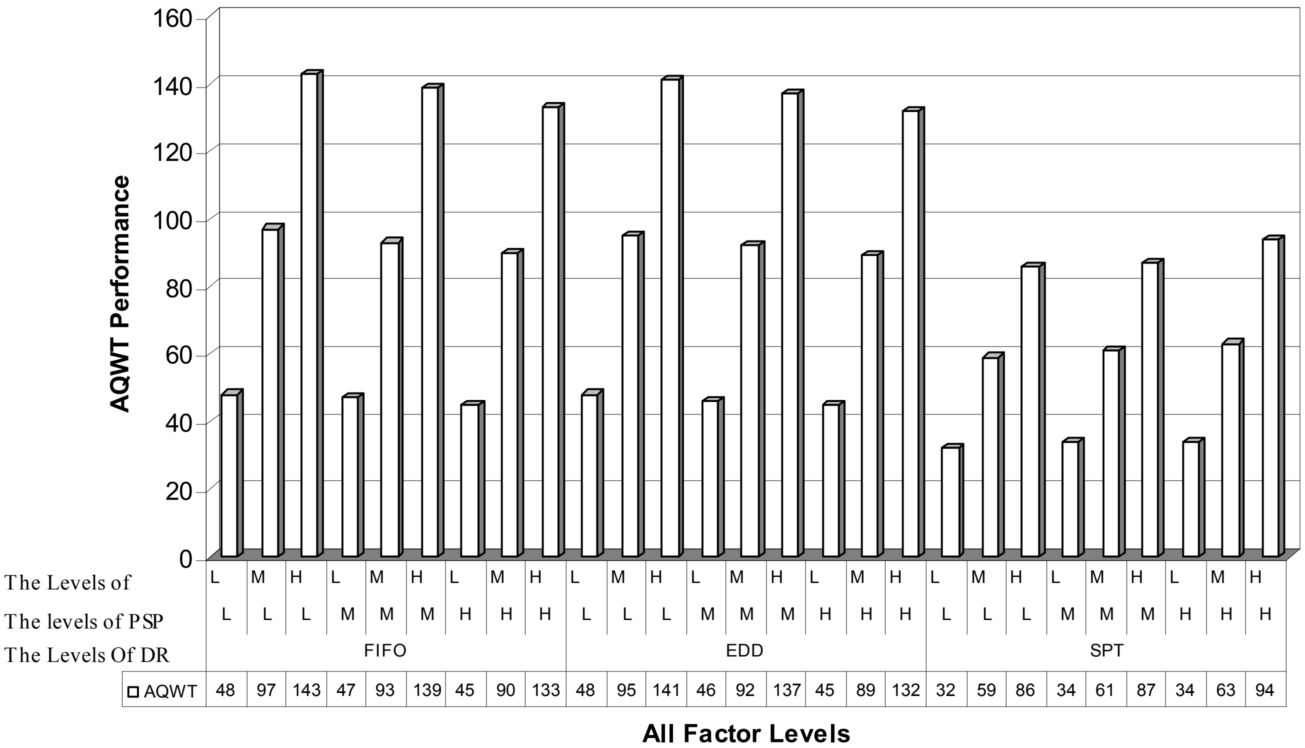


Figure A.6. AQWT Performance with AGGWNQ at low DF

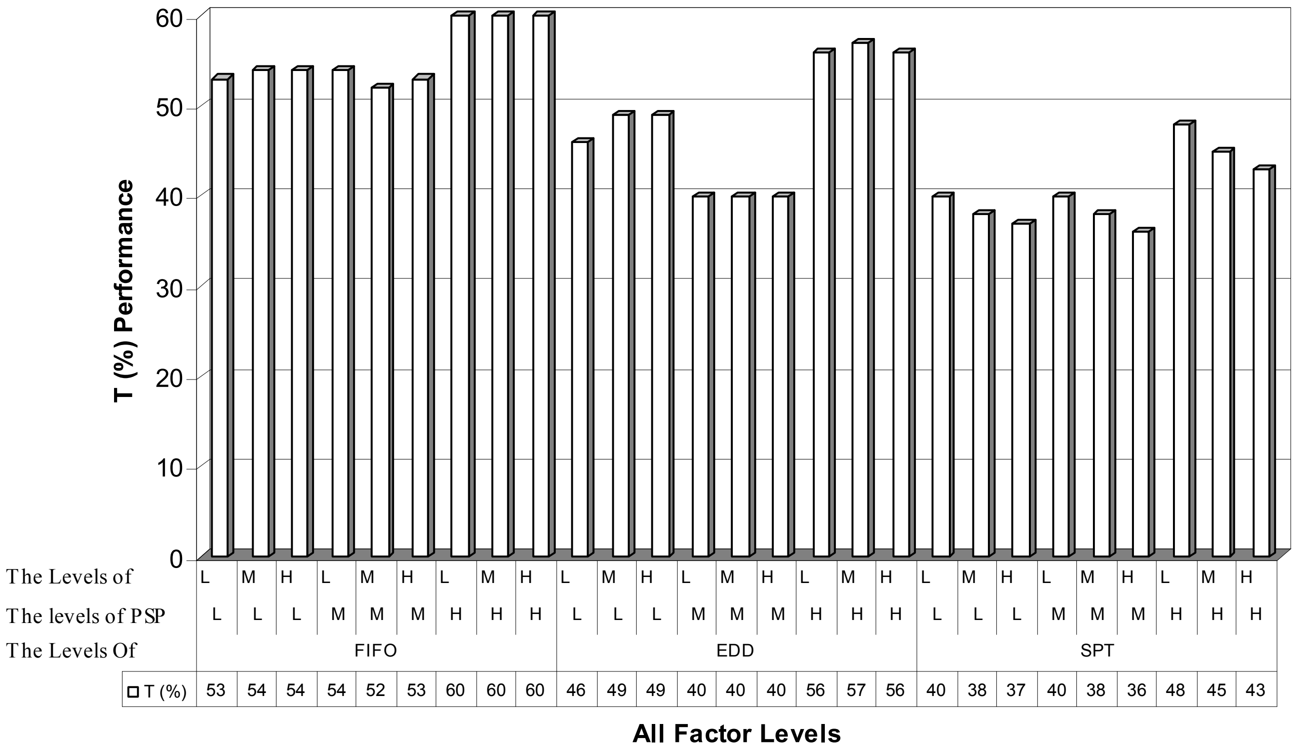


Figure A.7. T (%) Performance with AGGWNQ at low DF

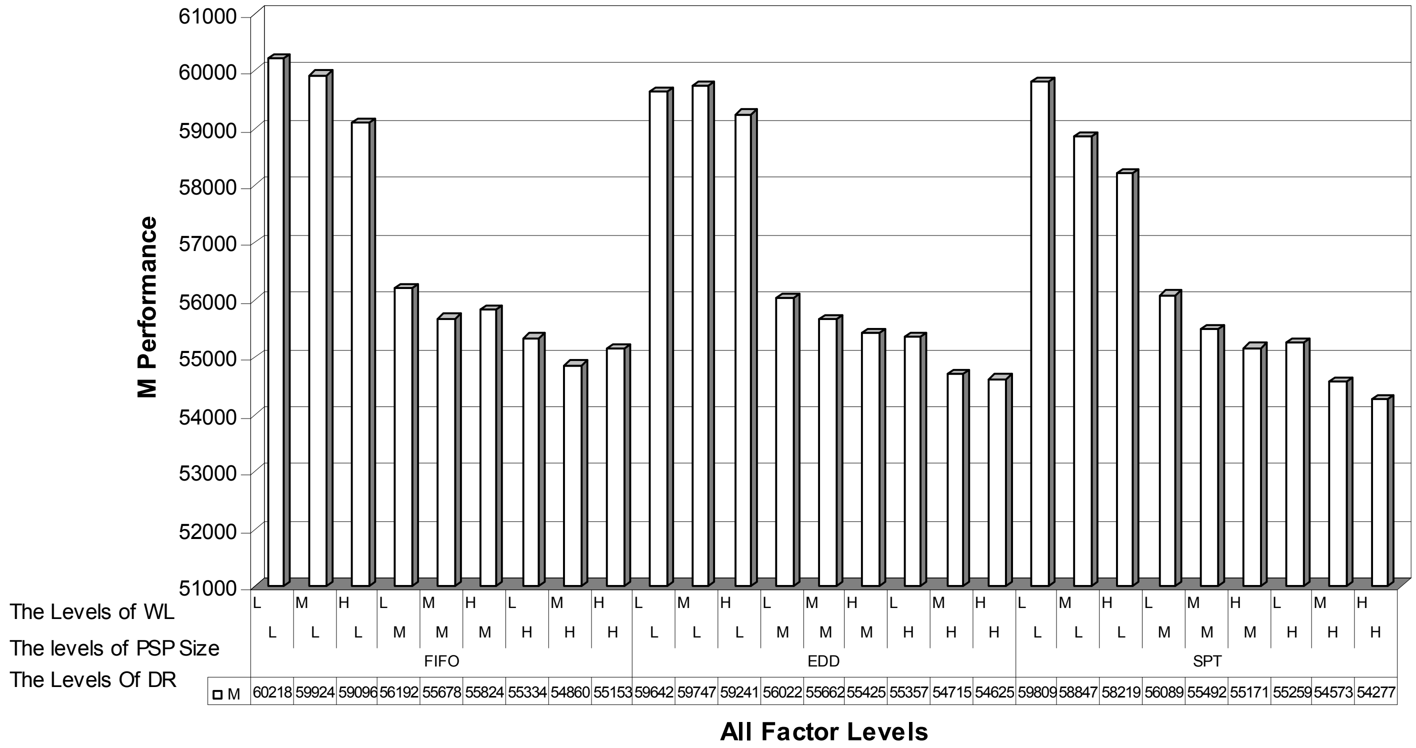


Figure A.8. M Performance with AGGWNQ at low DF

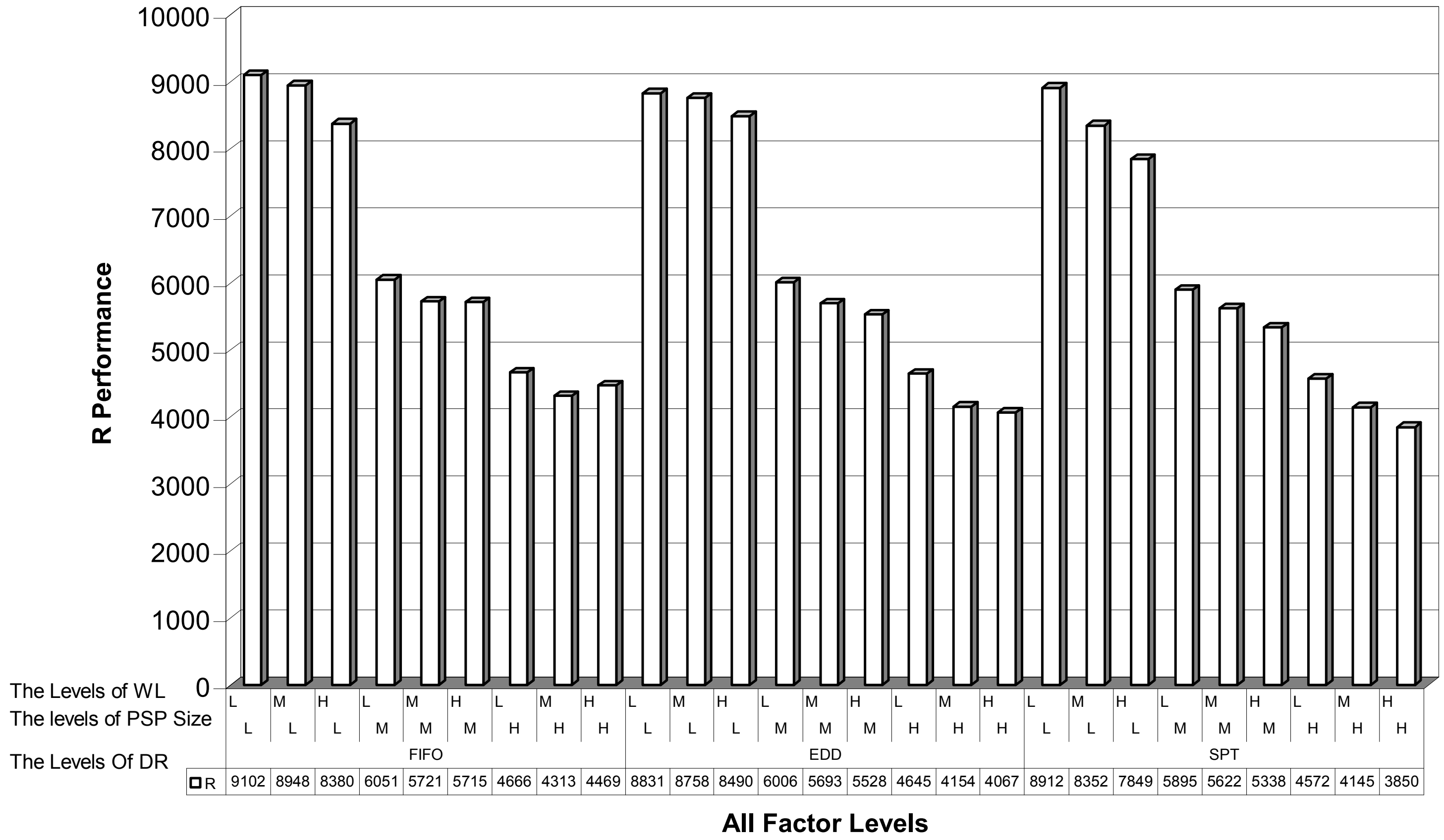


Figure A.9. R Performance with AGGWNQ at low DF

Table A.7. Measures of main Performances with AGGWNQ at low DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
0	AGGF	FIFO	1000	500	24	02	2465	349	2159	1249	5174	2489	-165	48	53	47	60218	9102
			1000	1000	23	02	2630	614	2092	1291	5324	2536	-165	97	54	46	59924	8948
			1000	1500	22	03	2785	867	2036	1392	5847	2722	-169	143	54	46	59096	8380
			2000	500	24	02	3145	339	2831	1000	5420	2304	-518	47	54	46	56192	6051
			2000	1000	22	01	3029	592	2478	844	5238	2069	-499	93	52	48	55678	5721
			2000	1500	22	01	3230	844	2449	801	5026	1953	-492	139	53	47	55824	5715
			3000	500	25	06	3974	330	3686	1432	5401	2597	-321	45	60	40	55334	4666
			3000	1000	23	06	3936	575	3449	1343	5149	2401	-239	90	60	40	54860	4313
			3000	1500	23	05	4001	815	3319	1154	4556	2150	-327	133	60	40	55153	4469
		EDD	1000	500	50	-24	2441	348	2098	1144	4694	2690	-151	48	46	54	59642	8831
			1000	1000	56	-27	2665	610	2064	1330	5411	2904	-185	95	49	51	59747	8758
			1000	1500	62	-31	2832	863	1978	1373	5512	3038	-208	141	49	51	59241	8490
			2000	500	75	-50	2929	337	2610	846	5110	2745	-430	46	40	60	56022	6006
			2000	1000	87	-64	2950	590	2387	755	4872	2492	-407	92	40	60	55662	5693
			2000	1500	91	-67	3126	835	2328	737	4854	2462	-420	137	40	60	55425	5528
			3000	500	54	-21	3792	329	3531	1317	5030	2539	-256	45	56	44	55357	4645
			3000	1000	58	-26	3702	568	3240	1223	4793	2323	-225	89	57	43	54715	4154
			3000	1500	71	-39	3667	805	3022	1014	3994	2052	-296	132	56	44	54625	4067
		SPT	1000	500	181	-152	2343	257	2114	1111	5731	3620	-542	32	40	60	59809	8912
			1000	1000	323	-294	2368	408	2012	1067	6475	4241	-897	59	38	62	58847	8352
			1000	1500	456	-424	2423	550	1952	1017	7172	4758	-1197	86	37	63	58219	7849
			2000	500	165	-137	2819	267	2578	696	5893	3036	-857	34	40	60	56089	5895
			2000	1000	290	-262	2667	419	2292	426	6118	3088	-1200	61	38	62	55492	5622
			2000	1500	388	-361	2677	559	2176	318	6554	3438	-1458	87	36	64	55171	5338
			3000	500	159	-126	3832	270	3602	1197	5930	3261	-743	34	48	52	55259	4572
			3000	1000	284	-252	3494	425	3139	774	5804	3074	-1124	63	45	55	54573	4145
			3000	1500	415	-383	3263	594	2767	401	5718	2948	-1491	94	43	57	54277	3850

A.4. The effect of the levels of WLL with AGGWNQ on other predetermined performance measures at intermediate DF

In Table A.8, the resulting measures of other shop performances with AGGWNQ OR mechanism at intermediate degree of flexibility is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed below.

<u>MAPE</u>: From Figure A.10., it is seen that the MAPE performance of the shop is significantly affected by different levels of DRs and WL. PSP size factor has no significant effect on the MAPE performance. By increasing the level of WL better MAPE performances obtained for FIFO DR. For other DRs, it is just the opposite. So, for both EDD and SPT DRs the low level of WL improves the MAPE performance. Let's focus on FIFO DR. In this case, from Figure A.10., it is apparent that the higher levels of WL provide better MAPE performance. It seems opposed to our suggestion up to here that the low level of WL improves the MAPE and other predetermined performance measures. But, this is not just the case. For example, consider the first factor combination, low PSP size and low WL. In this case the value of average MAPE and MLT value is 20% and 1681, respectively. Also, consider the second factor combination where the level of PSP size is 1000, WL is 1000. In this case the value of average MAPE and MLT value is 16% and 1800, respectively. If we prefer the higher levels of WL for the sake of an increase of 4% due date reliability performance we will face up to a decrease of 12,5% delivery speed which is not reasonable. The reasonable choice should be the first factor combination where the level of WL is low. Moreover, the best MAPE performance is attained with both EDD and SPT DRs. So there is no evidence against setting the level of WL to 500 in terms of MAPE performance measure.

<u>MLT</u>: The levels of WL have significant effect on MLT performance for all DR and PSP size factors combinations. MLT performance is improved for all factor combinations except SPT DR with higher levels of PSP size and WL. But, in the case the decrease in MLT values is outweighed by the increase in MAPE values which makes the choice of

these higher levels of WL inevitable. So, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure.

SFTT: The levels of WL and DRs have significant effect on the SFTT performance of the shop. From Figure A.12., it is apparent that the best SFTT performance is attained at low level of WL regardless of other factor levels. So there is no evidence against setting the level of WL to 500 in terms of SFTT performance measure.

APWT: The levels of WL have significant effect on APWT performance for all factor combinations. For higher levels of WL better APWT performances are obtained for all factor combinations. But, note that there is a trade-off between APWT performance and SFTT performance of the shop. It means that when we utilize higher levels of WL to obtain better APWT performance we always get worse SFTT performance. In this case, the MLT, which is the summation of APWT and SFTT, should be evaluated to decide on exact value of the level of WL. As mentioned above, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure and APWT performance as well.

AT: AT performance of the shop is affected by all factor combinations. For all factor combinations except SPT DR with low level of PSP size the low level of WL deteriorates the AT performance of the shop. But, note that the amount of improvement is not significant (i.e., by choosing high level of WL instead of low level of it we get a maximum improvement among all other factor combinations as 8.14 %). Even the maximum amount of difference between AT performances (i.e., for each PSP size, for each DR) due to the levels of WL does not constitutes an evidence against setting the level of WL to 500 in terms of AT performance measure.

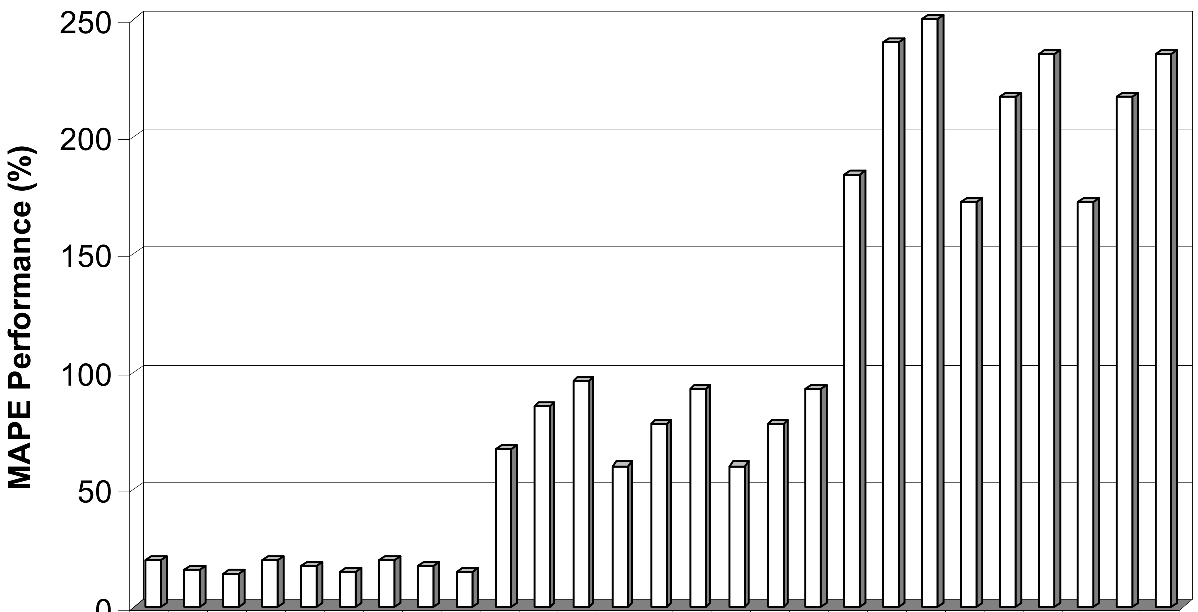
AQWT: The levels of WL and DR have significant effect on the AQWT performance of the shop. The low level of WL improves AQWT performance for all factor combinations considered. So, there is no evidence against setting the level of WL to 500 in terms of AQWT performance measure.

T (%): The T (%) performance is mainly affected by both WL and DR factors. For, FIFO DR, it is not affected by neither the levels of PSP size nor the levels of WL factors combinations. But, for EDD and SPT DRs it is mainly affected by the level of the WL. For SPT DR, selecting the low levels of WL results in better T(%) performance of the shop. But, this is not the case for EDD DR. Note that in this case as the levels of WL increases T(%) performance of the shop improves. But, decrease in the T(%) values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL inevitable for this case. So there is no evidence against setting the level of WL to 500 in terms of T (%) performance measure.

M: The M performance of the shop is affected by the levels of all factor combinations. For all factor combinations, except FIFO and EDD DR with low level of PSP size, the low level of WL improves the M performance of the shop. In the exceptional conditions, even the maximum performance deterioration with low level of WL is negligible. So there is no evidence against setting the level of WL to 500 in terms of M performance measure.

R: The R performance of the shop significantly affected by all factor combinations. It is affected mainly by the levels of the PSP size. Rejection of orders occurs only for low level of PSP size for each DRs. Note that the average total number of rejected orders is negligible even for the worst case. So, there is no evidence against setting the level of WL to 500 in terms of R performance measure.

Consequently, the low level of WL improves predetermined performance measures of the shop at intermediate degree of the flexibility. In Table A.12, all these results are summarized.



The Levels Of DR	FIFO									EDD									SPT								
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
MAPE (%)	20	16	14	20	17	15	20	17	15	67	85	96	60	78	93	60	78	93	184	240	250	172	217	235	172	217	235

Figure A.10. MAPE Performance with AGGWNQ at intermediate DF

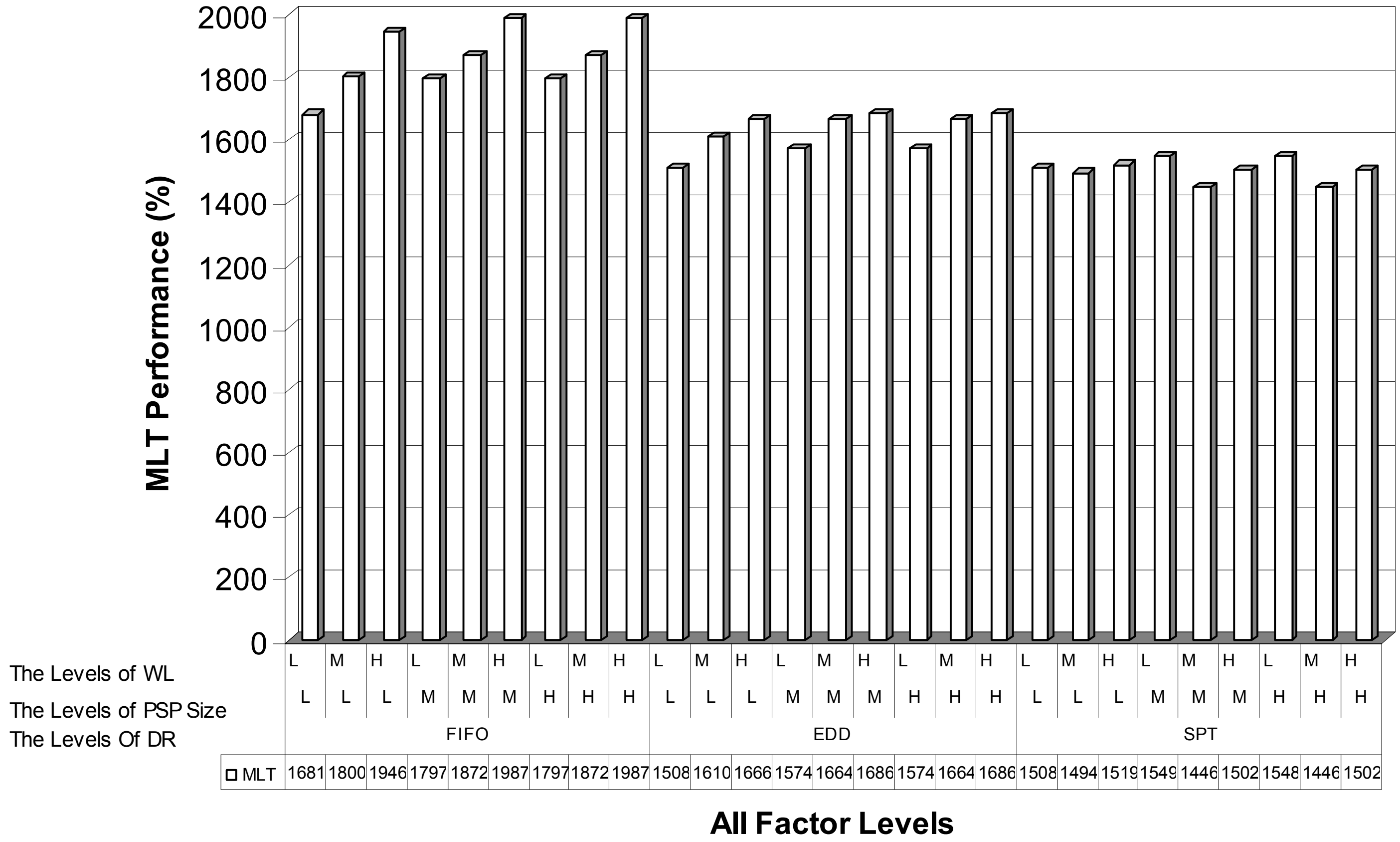
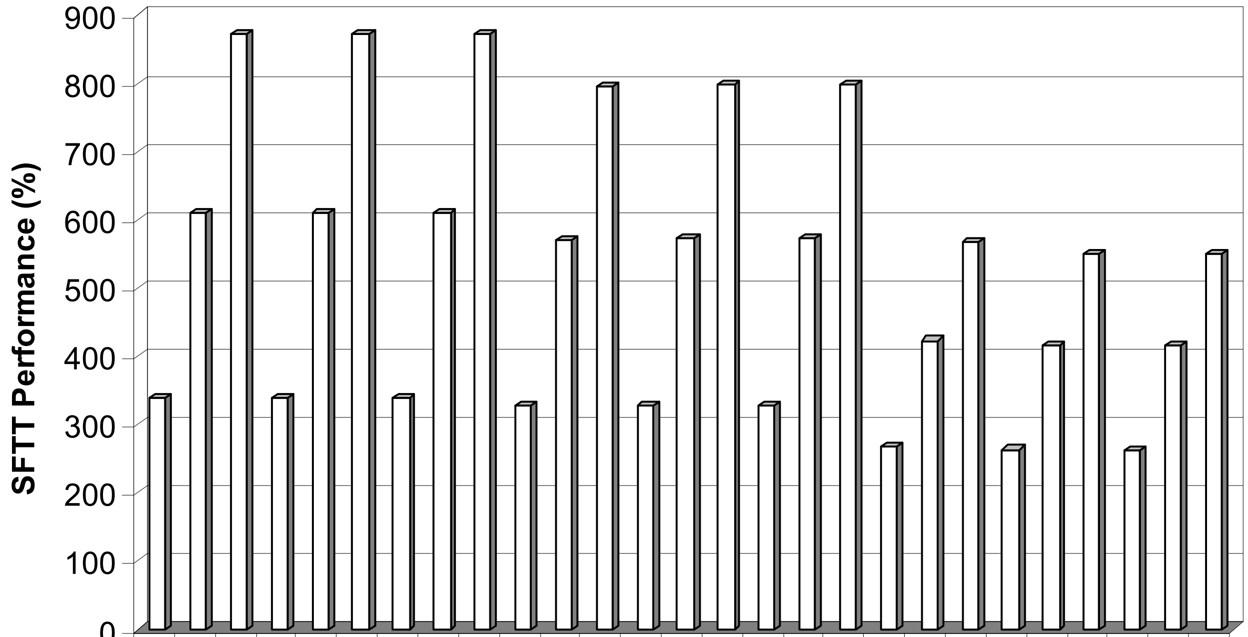


Figure A.11. MLT Performance with AGGWNQ at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
SFTT	339	610	871	338	610	871	338	610	871	328	570	796	327	572	799	327	572	799	267	423	566	263	415	551	262	415	551

Figure A.12. SFTT Performance with AGGWNQ at intermediate DF

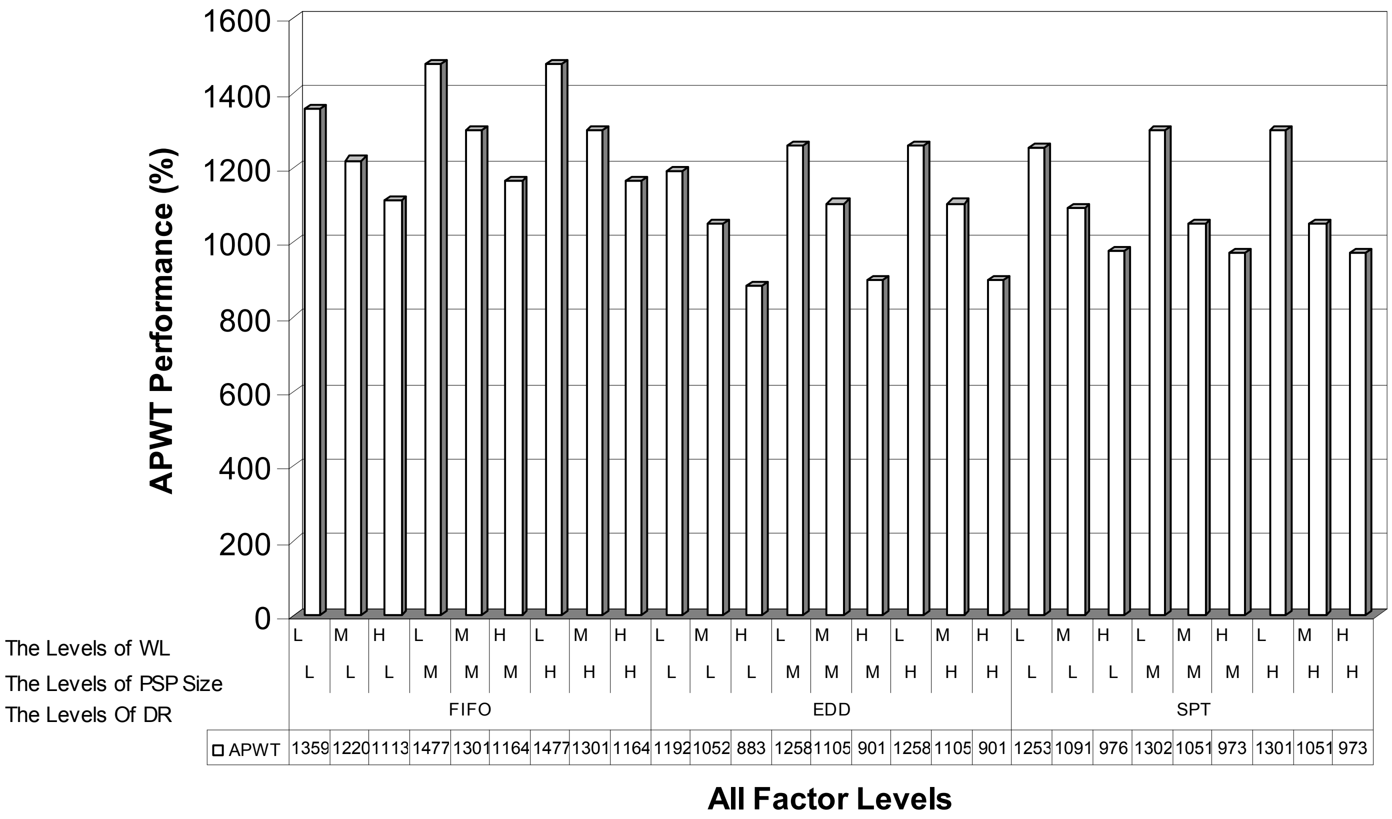


Figure A.13. APWT Performance with AGGWNQ at intermediate DF

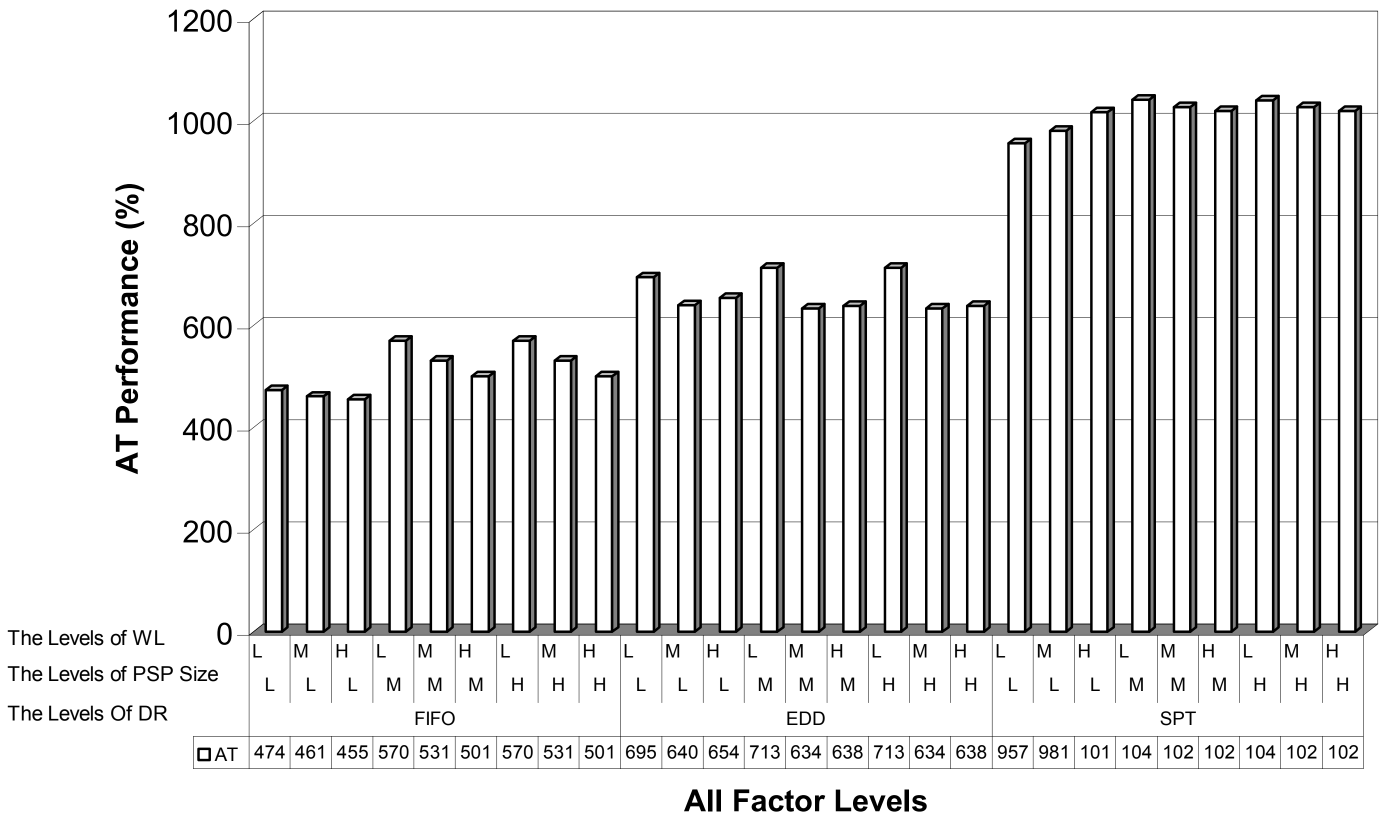
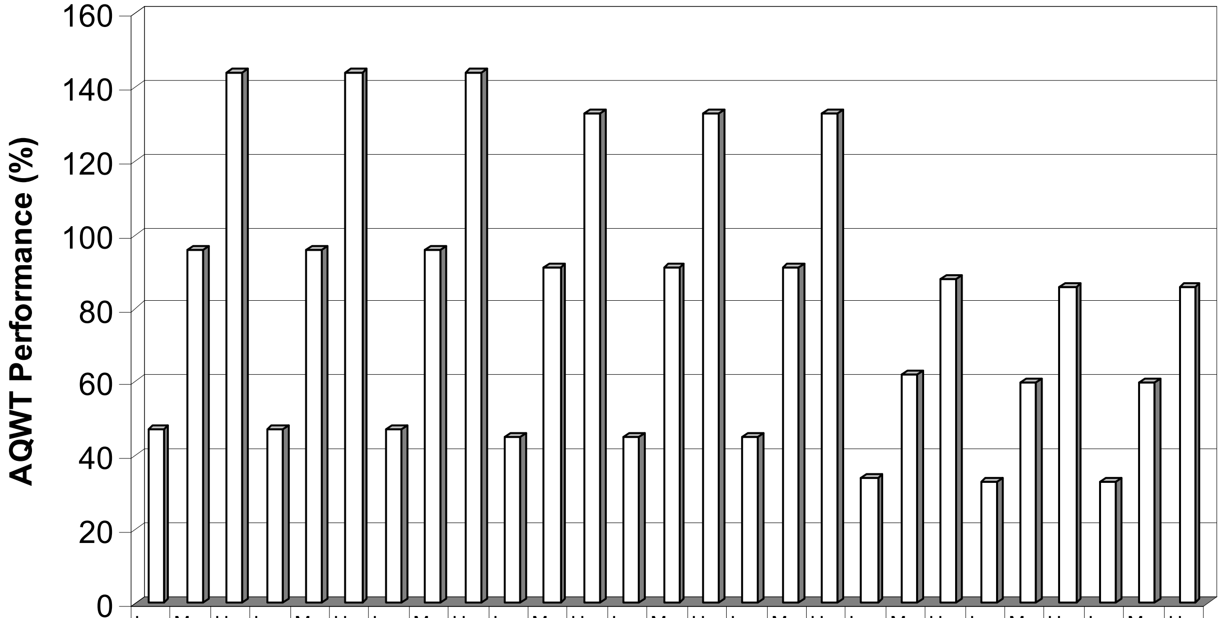
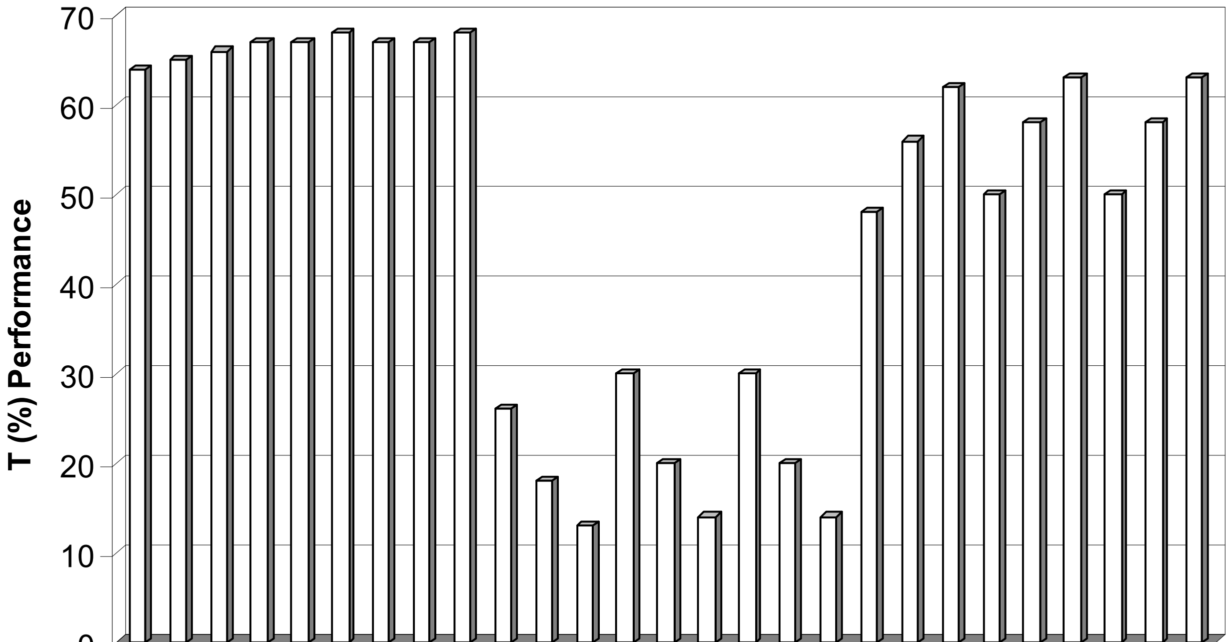


Figure A.14. AT Performance with AGGWNQ at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
AQWT	47	96	144	47	96	144	47	96	144	45	91	133	45	91	133	45	91	133	34	62	88	33	60	86	33	60	86

Figure A.15. AQWT Performance with AGGWNQ at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
T (%)	64	65	66	67	67	68	67	67	68	26	18	13	30	20	14	30	20	14	48	56	62	50	58	63	50	58	63

Figure A.16. T (%) Performance with AGGWNQ at intermediate DF

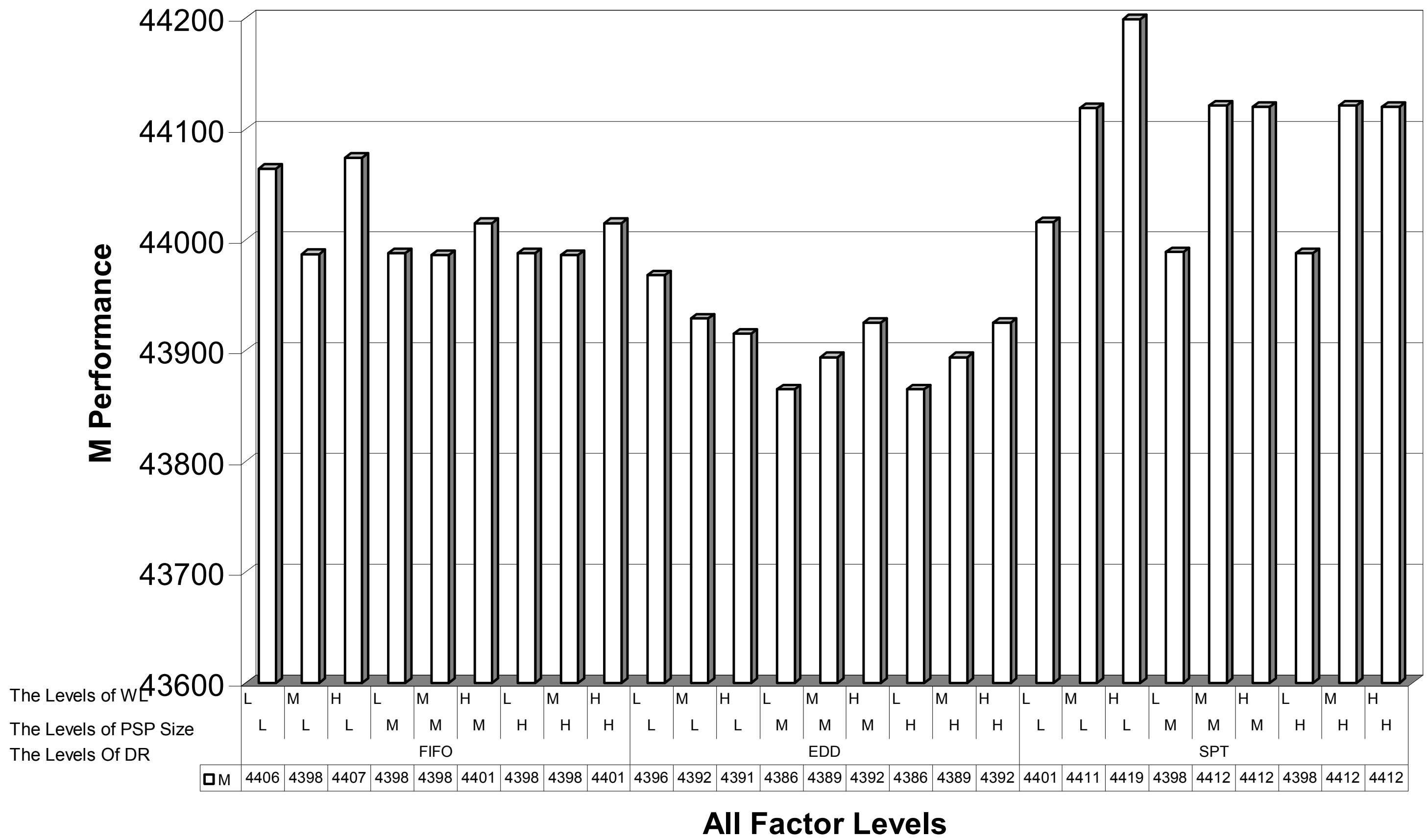
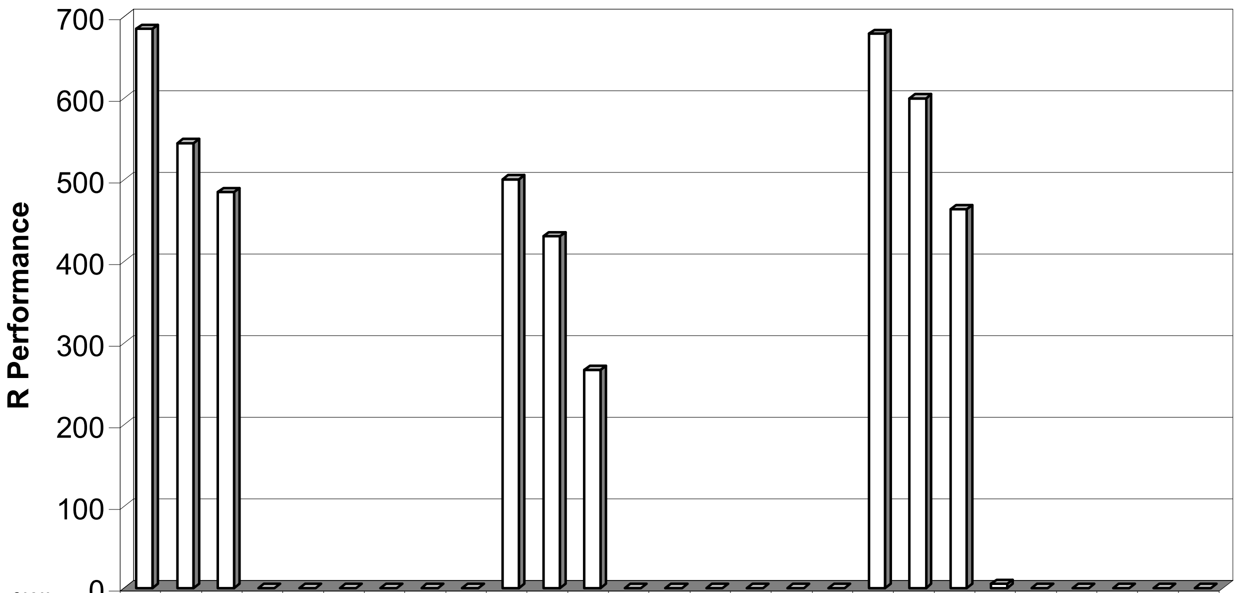


Figure A.17. M Performance with AGGWNQ at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
R	685	545	485	0	0	0	0	0	0	501	431	267	0	0	0	0	0	0	679	600	464	5	0	0	0	0	0

Figure A.18. R Performance with AGGWNQ at intermediate DF

Table A.8. Measures of main performances with AGGWNQ at intermediate DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
1	AGGWNQ	FIFO	1000	500	20	05	1681	339	1359	265	680	474	-106	47	64	36	44064	685
			1000	1000	16	06	1800	610	1220	259	677	461	-118	96	65	35	43987	545
			1000	1500	14	06	1946	871	1113	257	692	455	-122	144	66	34	44074	485
			2000	500	20	07	1797	338	1477	350	807	570	-100	47	67	33	43988	0
			2000	1000	17	07	1872	610	1301	323	789	531	-103	96	67	33	43986	0
			2000	1500	15	07	1987	871	1164	305	757	501	-108	144	68	32	44015	0
			3000	500	20	07	1797	338	1477	350	807	570	-100	47	67	33	43988	0
			3000	1000	17	07	1872	610	1301	323	789	531	-103	96	67	33	43986	0
			3000	1500	15	07	1987	871	1164	305	757	501	-108	144	68	32	44015	0
		EDD	1000	500	67	-57	1508	328	1192	27	670	695	-194	45	26	74	43968	501
			1000	1000	85	-79	1610	570	1052	-96	527	640	-249	91	18	82	43929	431
			1000	1500	96	-91	1666	796	883	-157	477	654	-274	133	13	87	43915	267
			2000	500	60	-49	1574	327	1258	80	696	713	-171	45	30	70	43865	0
			2000	1000	78	-71	1664	572	1105	-58	539	634	-230	91	20	80	43894	0
			2000	1500	93	-88	1686	799	901	-141	476	638	-266	133	14	86	43925	0
			3000	500	60	-49	1574	327	1258	80	696	713	-171	45	30	70	43865	0
			3000	1000	78	-71	1664	572	1105	-58	539	634	-230	91	20	80	43894	0
			3000	1500	93	-88	1686	799	901	-141	476	638	-266	133	14	86	43925	0
		SPT	1000	500	184	-151	1508	267	1253	92	2853	957	-698	34	48	52	44016	679
			1000	1000	240	-195	1494	423	1091	52	3564	981	-1151	62	56	44	44119	600
			1000	1500	250	-194	1519	566	976	93	3893	1018	-1419	88	62	38	44199	464
			2000	500	172	-137	1549	263	1302	167	2941	1042	-705	33	50	50	43989	5
			2000	1000	217	-170	1446	415	1051	128	3475	1028	-1107	60	58	42	44121	0
			2000	1500	235	-178	1502	551	973	136	3768	1020	-1391	86	63	37	44120	0
			3000	500	172	-137	1548	262	1301	167	2940	1041	-705	33	50	50	43988	0
			3000	1000	217	-170	1446	415	1051	128	3475	1028	-1107	60	58	42	44121	0
			3000	1500	235	-178	1502	551	973	136	3768	1020	-1391	86	63	37	44120	0

A.5. The effect of the levels of WLL with AGGWNQ on other predetermined performance measures at high DF

In Table A.9, the resulting measures of other shop performances with AGGWNQ OR mechanism at high degree of flexibility is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed below.

<u>MAPE</u>: From Figure A.19, it is seen that the MAPE performance of the shop is significantly affected by different levels of DRs and WL. PSP size factor has almost no effect on the MAPE performance. For FIFO dispatching rule, MAPE performance is not significantly affected by the levels of WL. For other DRs, as the level of WL decreases MAPE performance improves. So there is no evidence against setting the level of WL to 500 in terms of MAPE performance measure.

<u>MLT</u>: The MLT performance is mainly affected by WL and DR. The levels of WL affect the MLT performance for all DR and PSP size factors combinations. For all levels of PSP size with SPT and FIFO DRs the low level of WL improves the MLT performance. But, this is just the opposite for EDD DR. However, in this case the amount of improvement on the MLT performance for higher levels of WL is outweighed by the amount of deterioration on the MAPE performance. So, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure.

<u>SFTT</u>: The levels of WL have significant effect on the SFTT performance of the shop. Neither PSP size nor the DR factors has significant effect on the SFTT performance of the shop. From Figure A.21, it is apparent that as the best SFTT is attained at low WL. So there is no evidence against setting the level of WL to 500 in terms of SFTT performance measure.

<u>APWT</u>: The APWT performance is significantly affected by all factors. For each DR, the low level of PSP size minimizes APWT. The other levels of PSP size factor do not differ in terms of APWT performance for each DR. This is mainly because for medium and high level of PSP sizes all jobs are accepted which causes the PSP size factor to lose

its control. The low level of WL worsens the APWT performance for each level of DR whereas higher levels of it improve. But, note that there is a trade-off between APWT performance and SFTT performance of the shop. It means that when we utilize higher levels of WL to obtain better APWT performance we always get worse SFTT performance. In this case, the MLT performance of the shop, which is the summation of APWT and SFTT performances, should be evaluated to decide on appropriate value of the level of WL. As mentioned above, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure and APWT performance as well.

AT: AT performance of the shop is affected by all factor combinations. For FIFO and EDD DRs, the low level of WL improves the AT performance of the shop regardless of the PSP size factor. But, For SPT DRs it is not just the case. Note that, for SPT DR the AT performance of the shop is inevitable even for the best case. Other than this, the amount of improvement obtained by choosing high level of WL instead of low level of is not significant. So, there is no evidence against setting the level of WL to 500 in terms of AT performance measure.

AQWT: The levels of WL and DRs have significant effect on the AQWT performance of the shop. As the level of WL decreases the AQWT performance improves for all other factors combinations. So, there is no evidence against setting the level of WL to 500 in terms of AQWT performance measure.

T (%): The T (%) performance is mainly affected by both DR and WL. For, FIFO DR it is not affected neither the levels of PSP size nor the levels of WL factors combinations. But, for EDD and SPT DRs it is mainly affected by the level of the WL. For SPT DR, selecting the low levels of WL results in better T(%) performance of the shop. But, this is not the case for EDD DR. Note that in this case as the levels of WL increases T(%) values decreases. But, decrease in the T(%) values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL unacceptable for this case. So there is no evidence against setting the level of WL to 500 in terms of T (%) performance measure.

M: Makespan performance of the shop is affected by all factors. For SPT and FIFO DR the low level of WL improves the M performance. For EDD DR the low level of WL deteriorates M performance. But, as mentioned before, high levels of WL and EDD DR result in unacceptable due date reliability. Also, note that the amount of difference between M with low WL and M with high WL is negligible. So, there is no evidence against setting the level of WL to 500 in terms of M performance measure.

R: The levels of WL have significant effect on R performance of the shop. But, note that it is affected mainly by the levels of the PSP size. Rejection of orders occurs only when the level of PSP size is set to 1000 for each DRs and WL. Note that the average total number of rejected orders is negligible even for the worst case. So, there is no evidence against setting the level of WL to 500 in terms of R performance measure.

Consequently, the low level of WL improves predetermined main performance measures of the shop at high DF. All these results are summarized in Table A.8.

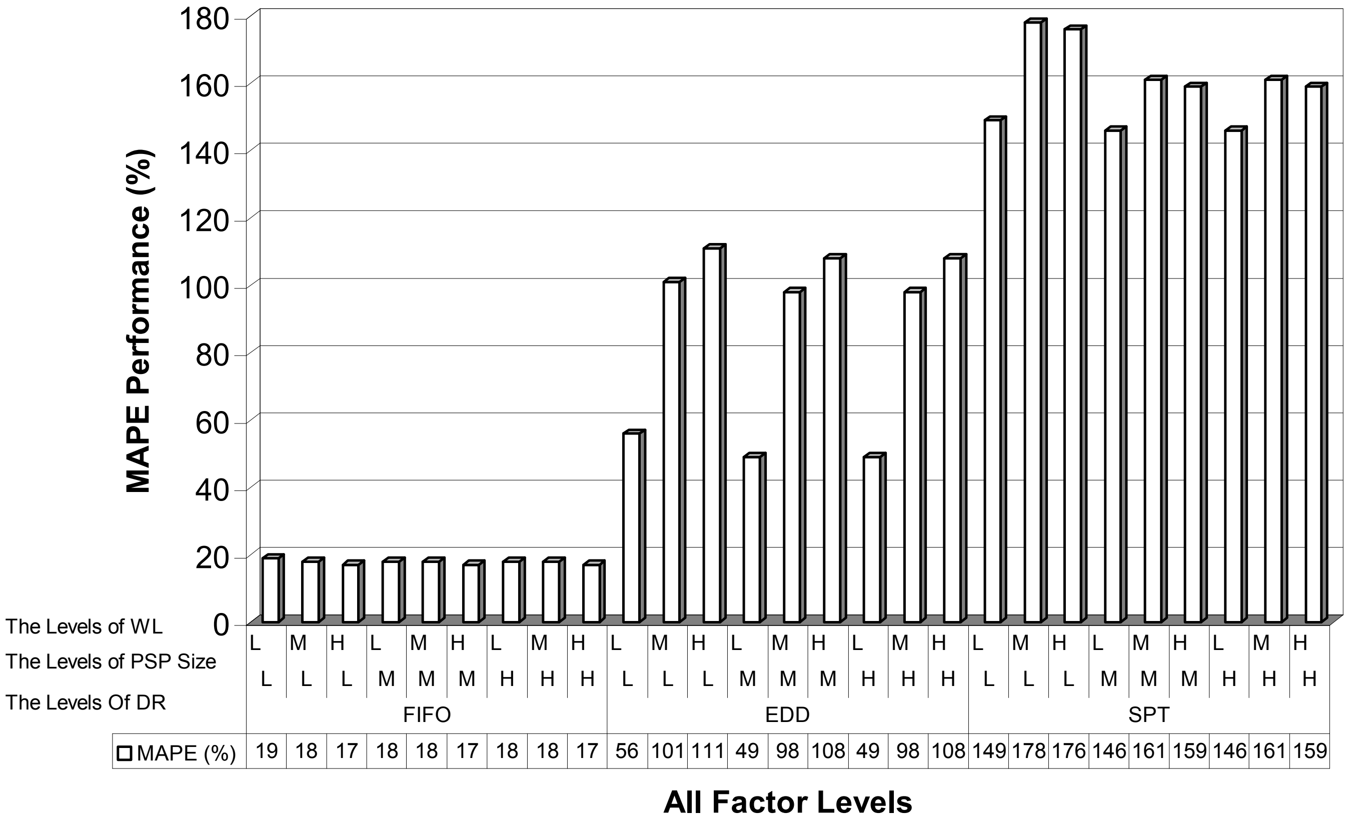


Figure A.19. MAPE Performance with AGGWNQ at high DF

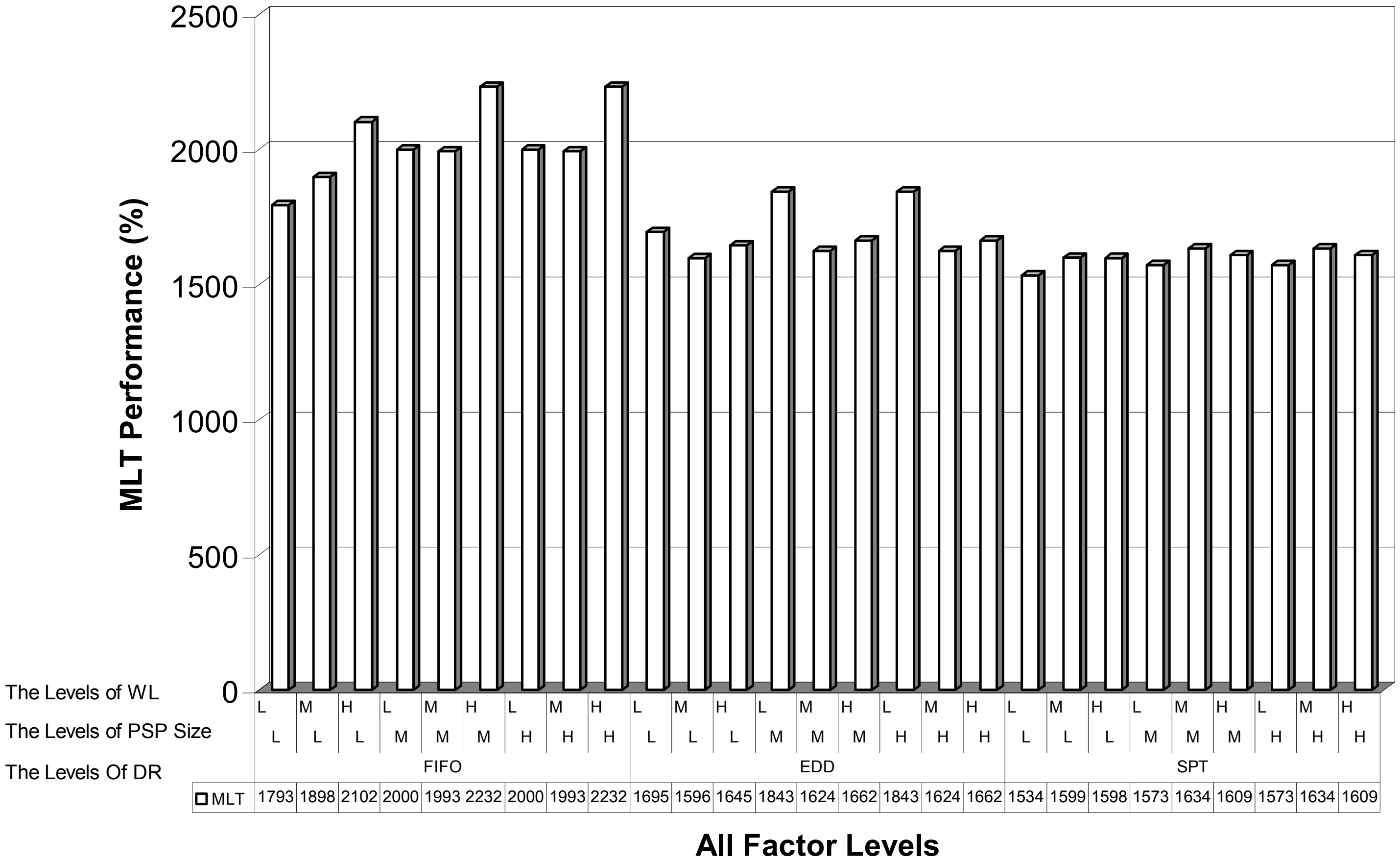


Figure A.20. MLT Performance with AGGWNQ at high DF

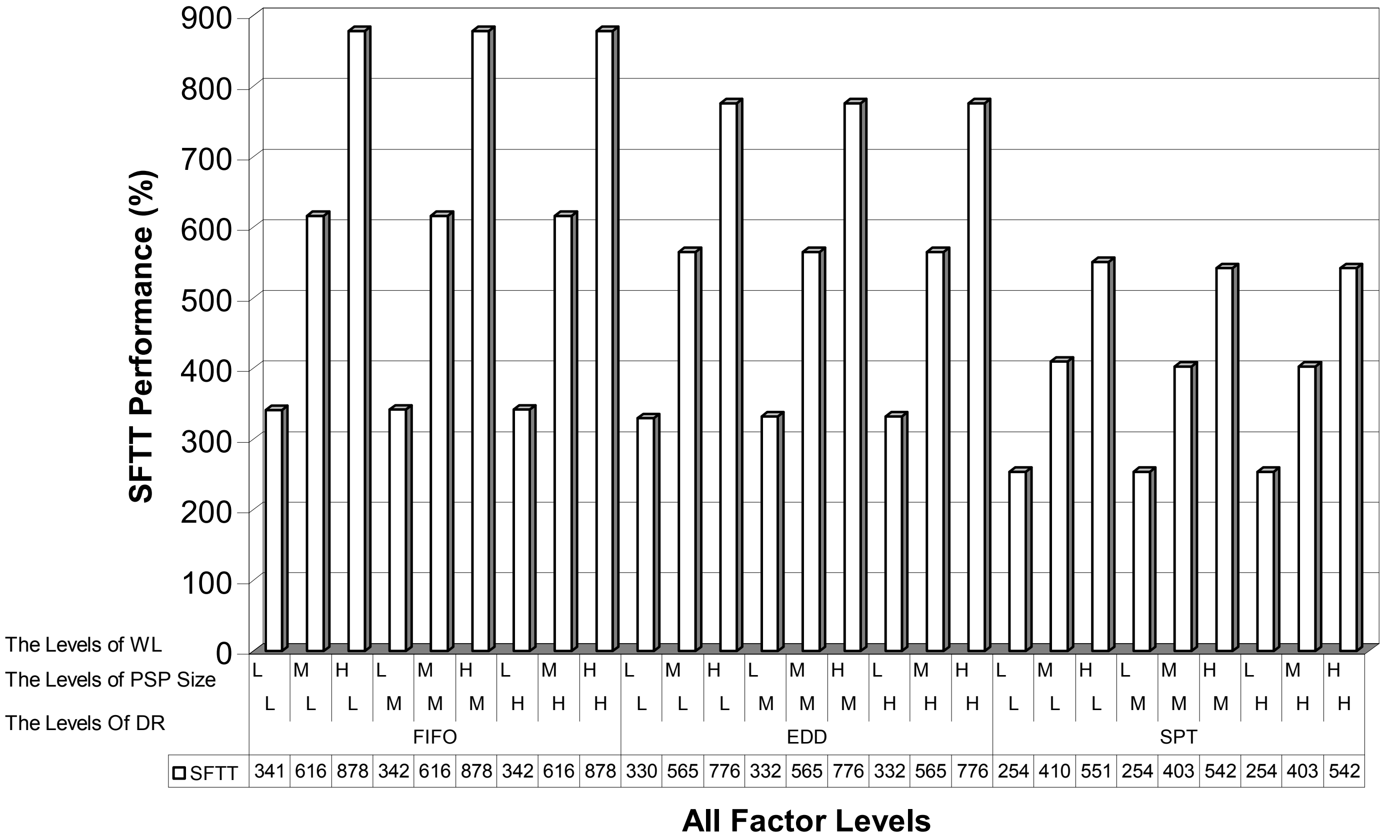


Figure A.21. SFTT Performance with AGGWNQ at high DF

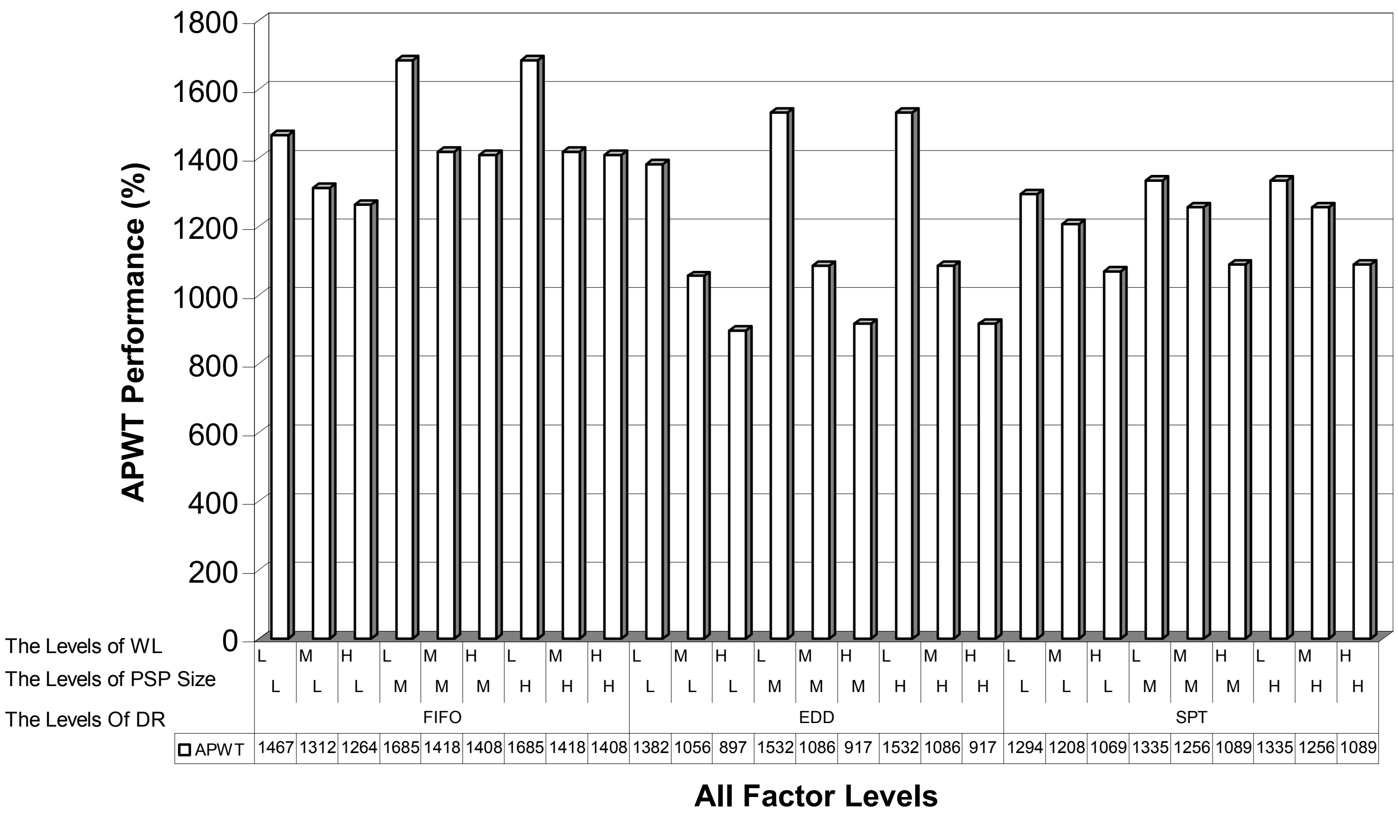


Figure A.22. APWT Performance with AGGWNQ at high DF

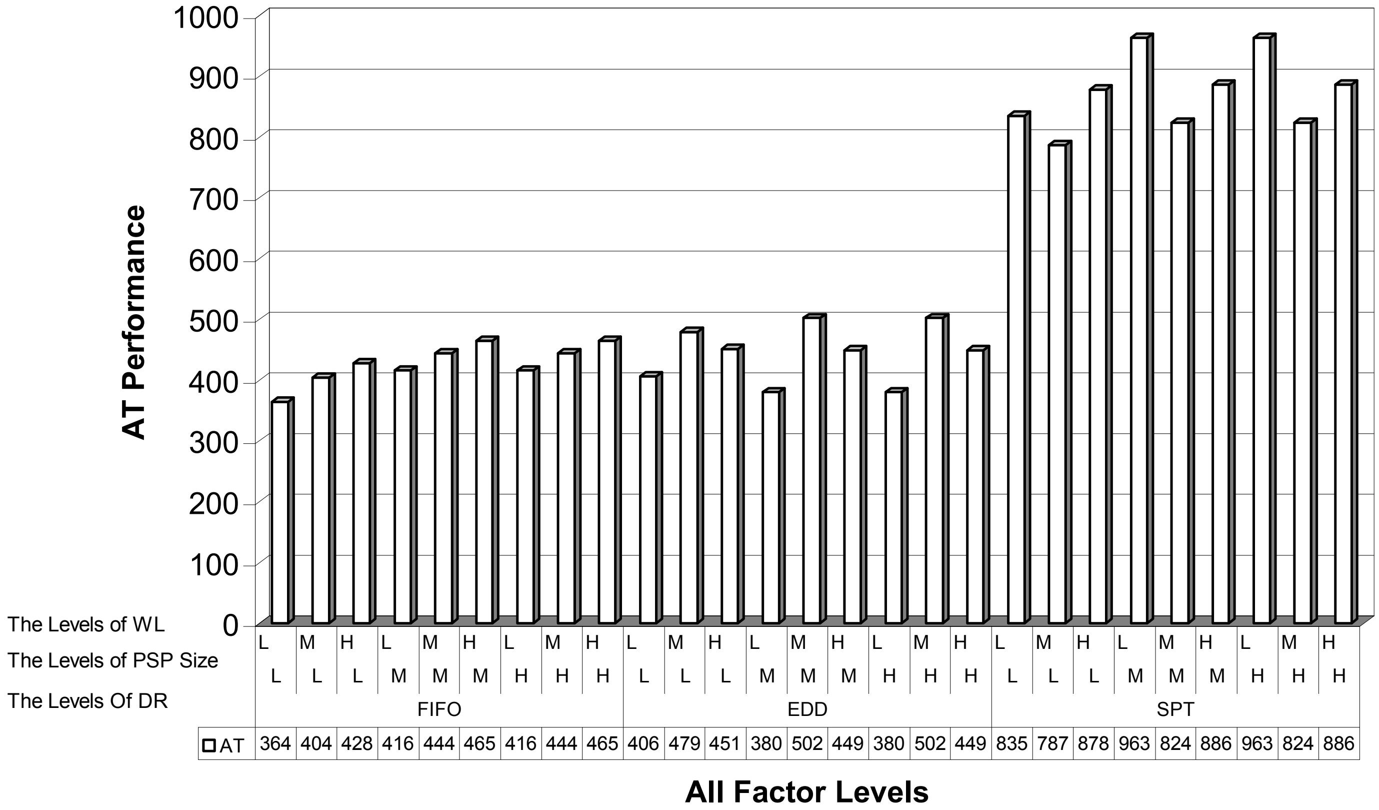


Figure A.23. AT Performance with AGGWNQ at high DF

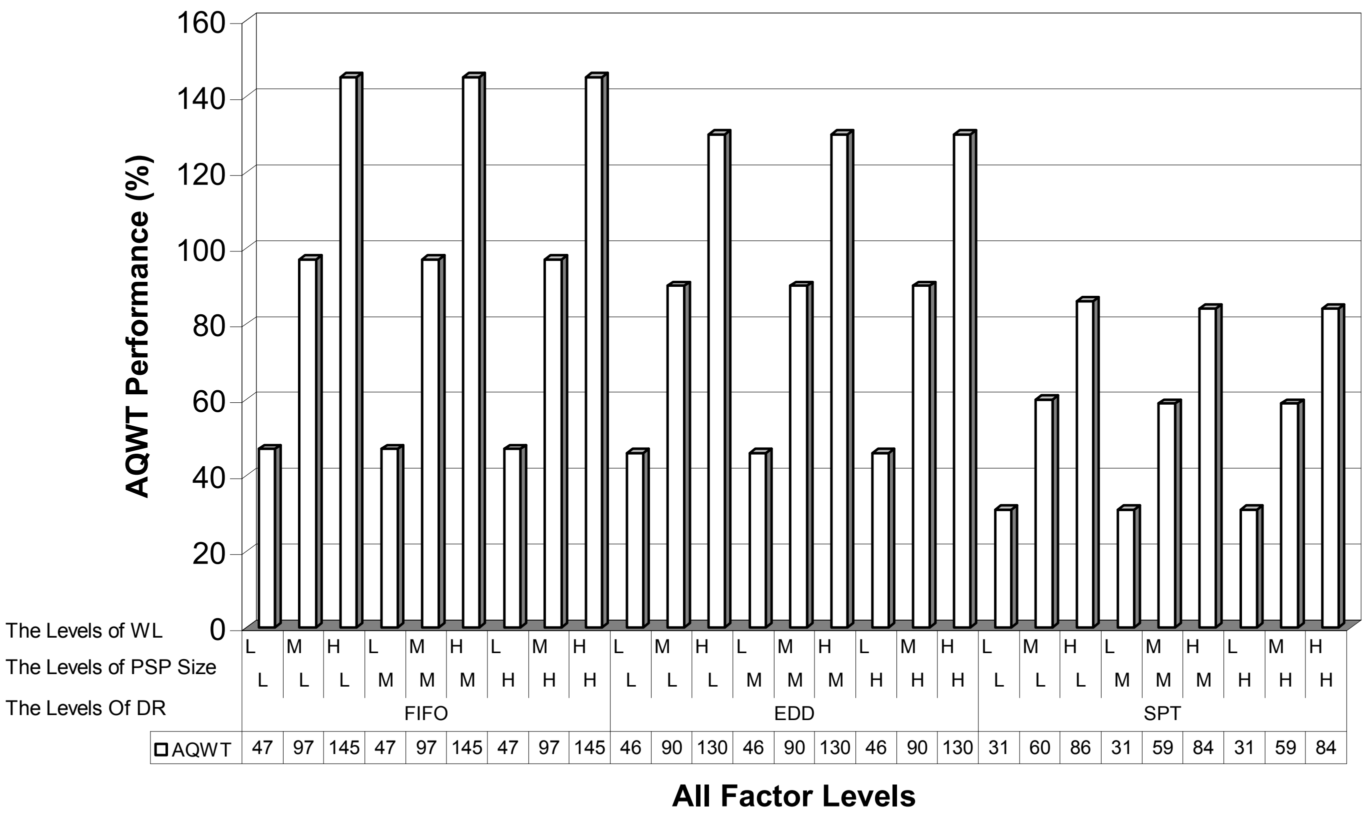


Figure A.24. SFTT Performance with AGGWNQ at high DF

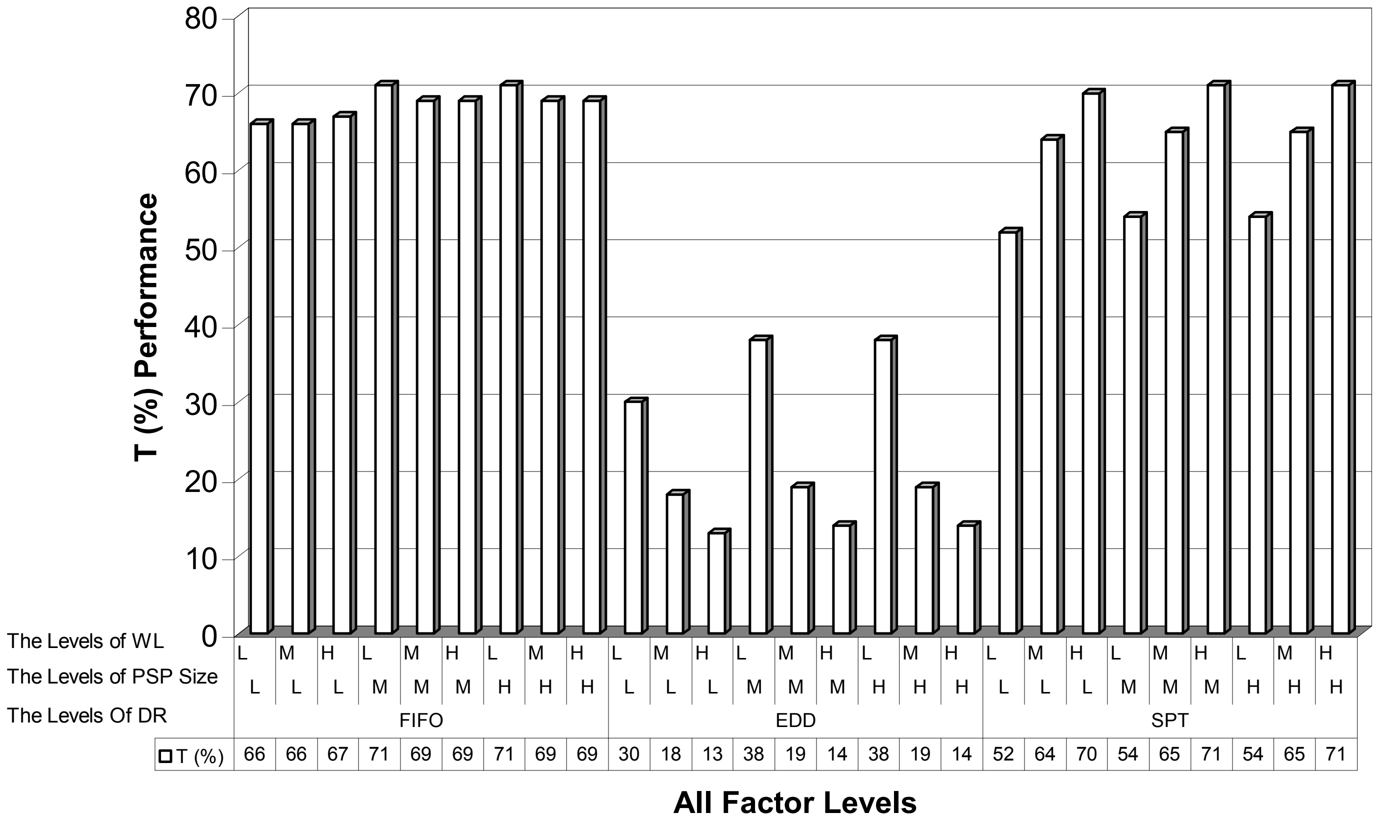


Figure A.25. T (%) Performance with AGGWNQ at high DF

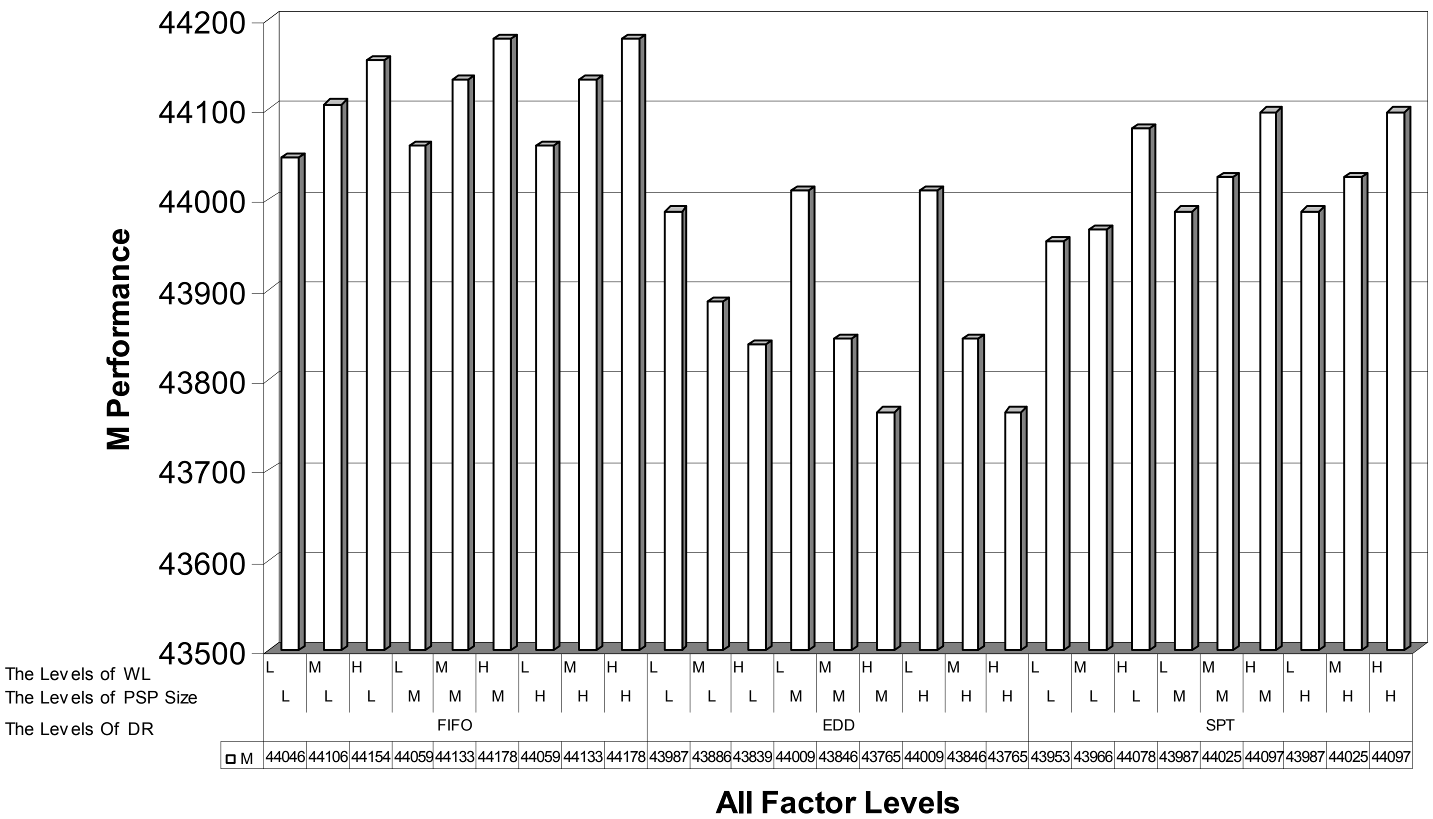


Figure A.26. M Performance with AGGWNQ at high DF

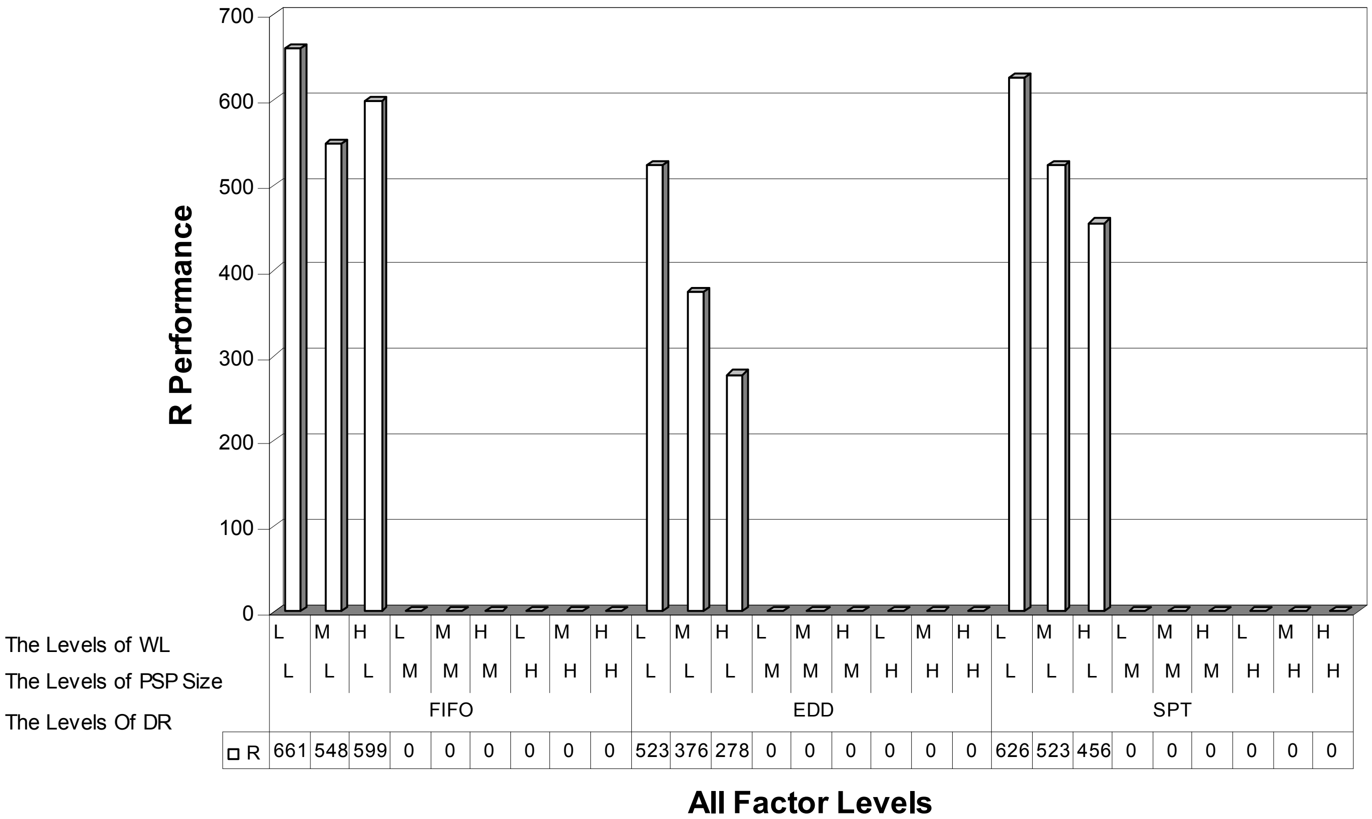


Figure A.27. R Performance with AGGWNQ at high DF

Table A.9. Measures of main Performances with AGGWNQ at high DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
2	AGGWNQ	FIFO	1000	500	19	06	1793	341	1467	186	441	364	-159	47	66	34	44046	661
			1000	1000	18	06	1898	616	1312	204	507	404	-185	97	66	34	44106	548
			1000	1500	17	07	2102	878	1264	224	516	428	-190	145	67	33	44154	599
			2000	500	18	08	2000	342	1685	253	472	416	-145	47	71	29	44059	0
			2000	1000	18	07	1993	616	1418	249	541	444	-178	97	69	31	44133	0
			2000	1500	17	08	2232	878	1408	268	557	465	-180	145	69	31	44178	0
			3000	500	18	08	2000	342	1685	253	472	416	-145	47	71	29	44059	0
			3000	1000	18	07	1993	616	1418	249	541	444	-178	97	69	31	44133	0
			3000	1500	17	08	2232	878	1408	268	557	465	-180	145	69	31	44178	0
		EDD	1000	500	56	-45	1695	330	1382	-60	456	406	-259	46	30	70	43987	523
			1000	1000	101	-92	1596	565	1056	-250	538	479	-412	90	18	82	43886	376
			1000	1500	111	-105	1645	776	897	-301	502	451	-418	130	13	87	43839	278
			2000	500	49	-37	1843	332	1532	-5	438	380	-228	46	38	62	44009	0
			2000	1000	98	-89	1624	565	1086	-230	554	502	-403	90	19	81	43846	0
			2000	1500	108	-102	1662	776	917	-281	498	449	-401	130	14	86	43765	0
			3000	500	49	-37	1843	332	1532	-5	438	380	-228	46	38	62	44009	0
			3000	1000	98	-89	1624	565	1086	-230	554	502	-403	90	19	81	43846	0
			3000	1500	108	-102	1662	776	917	-281	498	449	-401	130	14	86	43765	0
		SPT	1000	500	149	-114	1534	254	1294	85	3007	835	-738	31	52	48	43953	626
			1000	1000	178	-130	1599	410	1208	50	3613	787	-1267	60	64	36	43966	523
			1000	1500	176	-117	1598	551	1069	145	3810	878	-1543	86	70	30	44078	456
			2000	500	146	-109	1573	254	1335	188	3058	963	-728	31	54	46	43987	0
			2000	1000	161	-113	1634	403	1256	108	3510	824	-1245	59	65	35	44025	0
			2000	1500	159	-99	1609	542	1089	193	3667	886	-1494	84	71	29	44097	0
			3000	500	146	-109	1573	254	1335	188	3058	963	-728	31	54	46	43987	0
			3000	1000	161	-113	1634	403	1256	108	3510	824	-1245	59	65	35	44025	0
			3000	1500	159	-99	1609	542	1089	193	3667	886	-1494	84	71	29	44097	0

A.6. The effect of the levels of WL with WCWT on other predetermined performance measures at low DF

In Table A.10, the resulting measures of other shop performances with WCWT OR mechanism at low DF is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed below.

<u>MAPE</u>: From Figure A.28., it is apparent that the MAPE performance of the shop is significantly affected by all factors. For FIFO DR, the levels of WL have no significant effect on MAPE performance of the shop. But, for both EDD and SPT DRs, the best MAPE performance is attained at low WL regardless of the levels of PSP size. So there is no evidence against setting the level of WL to 500 in terms of MAPE performance measure.

<u>MLT</u>: The levels of WL have significant effect on the MLT performance only when FIFO and SPT DRs used. For these DRs, the low level of WL improves MLT performance of the shop. When EDD DR is used the levels of WL has no significant effect. However, higher levels of WL improve MLT performance. Note that, in this case the decrease in MLT values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL inevitable. So, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure.

<u>SFTT</u>: The WL has significant effect on the SFTT performance of the shop. From Figure A.30., it is apparently seen that the best MAPE performance is attained at low WL. So, there is no evidence against setting the level of WL to 500 in terms of SFTT performance measure.

<u>APWT</u>: From Figure A.31., the APWT performance of the shop is significantly affected by the levels of PSP size factor. For each DR, the levels of WL have negligible effect on APWT performance at lower levels of PSP size. The worst APWT performance is obtained for high levels of PSP size for each DR. The effect of the levels of WL increases as the level of PSP size increases. At low and medium PSP sizes, as the level

of WL increases the APWT performance improves except EDD DR with medium PSP size. Also, at high PSP size the low level of WL worsens the APWT performance. Note that, even the biggest amount of difference between the APWT with low WL and APWT with high WL is negligible (i.e., 230 time units is obtained at high PSP size for FIFO DR). Also, note that there is a trade-off between APWT performance and SFTT performance of the shop. It means that increasing the levels of WL improves APWT performance but worsens SFTT performance. In this case, the MLT performance which is summation of APWT and SFTT performances must be evaluated. As mentioned above, there is no evidence against setting the level of WL to 500 in terms of MLT performance measure and APWT performance as well.

AT: From Figure A.32., it is apparent that AT performance of the shop affected by all factors. For FIFO DR the levels of the WL have no significant effect on the AT performance at low and intermediate PSP sizes. At high PSP size the level of WL significantly affects the AT performance. For EDD dispatching rule with low PSP size, the worst AT performance is attained at low WL. Changing from low to higher PSP sizes the levels of WL lose its effect on the AT performance. For SPT DR, the worst AT performance is attained at low WL and low PSP size. However, for both medium and high levels of PSP size, the best AT performance is obtained at low WL. Determining the effect of the levels of WL on AT performance is somewhat cumbersome. But, there is no evidence against setting the level of WL to 500 in terms of AT performance measure.

AQWT: All factors have significant effect on the AQWT performance of the shop. The best AQWT performance is obtained at low WL regardless of other factor combinations. So, there is no evidence against setting the level of WL to its low level in terms of AQWT performance measure.

T (%): The T (%) performance of the shop is not significantly affected by the levels of WL. It is mainly affected by both PSP size and DR factors. So there is no evidence against setting the level of WL to its low level in terms of T (%) performance measure.

M: Makespan performance of the shop is mainly affected by the levels of PSP size factor. Both the levels of DRs and the levels of WL have negligible effect on the M performance of the shop. So, there is no evidence against setting the level of WL to its low level in terms of M performance measure.

R: R performance of the shop is mainly affected by the levels of PSP size. Both the levels of DRs and the levels of WL have negligible effect on the R performance of the shop. So, there is no evidence against setting the level of WL to its low level in terms of R performance measure.

Consequently, measures of performances improve at low WL and low DF with WCWT OR mechanism. In Table A.14, all these results are summarized for all factor combinations according to each predetermined performance measure.

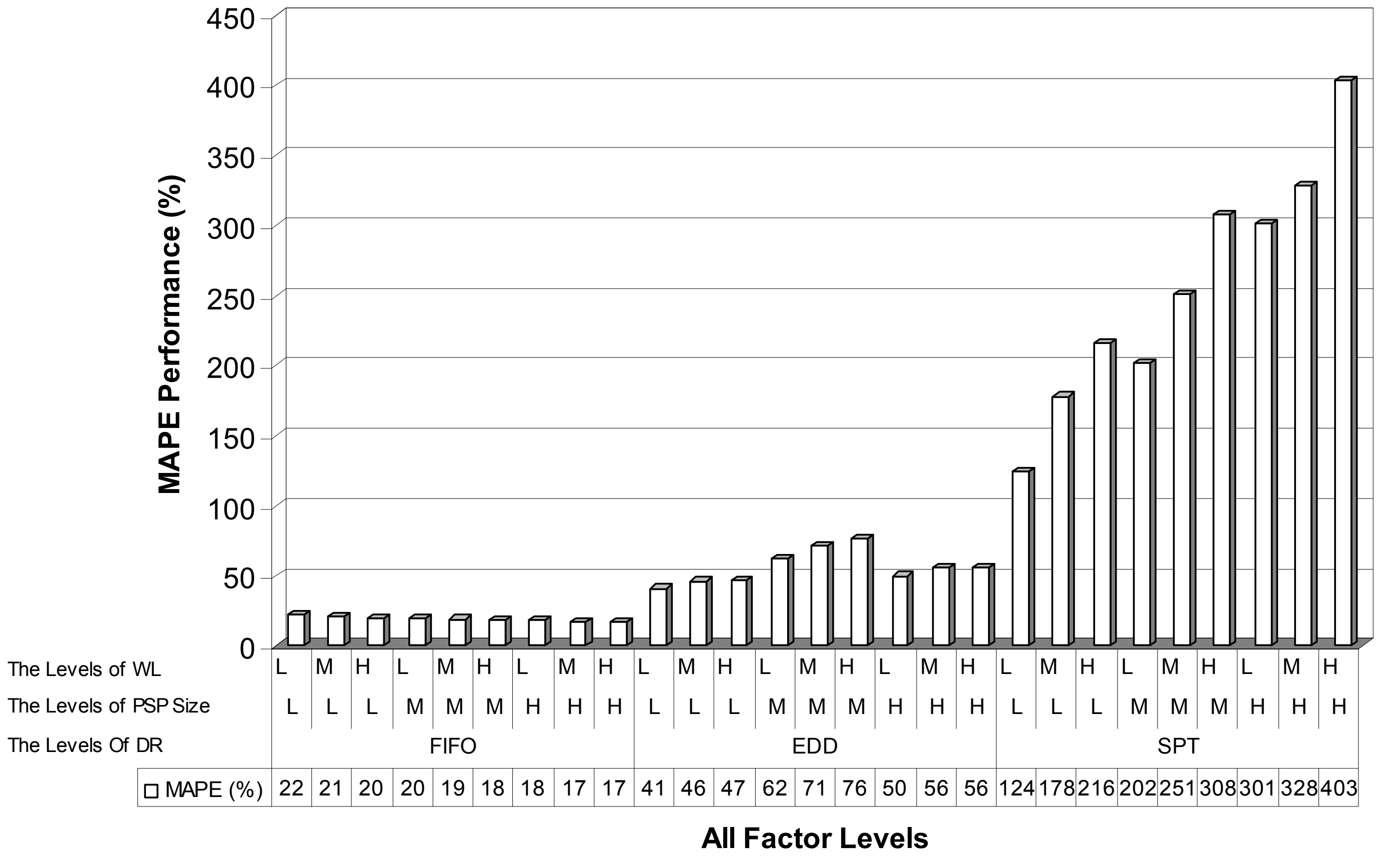


Figure A.28. MAPE Performance with WCWT at low DF

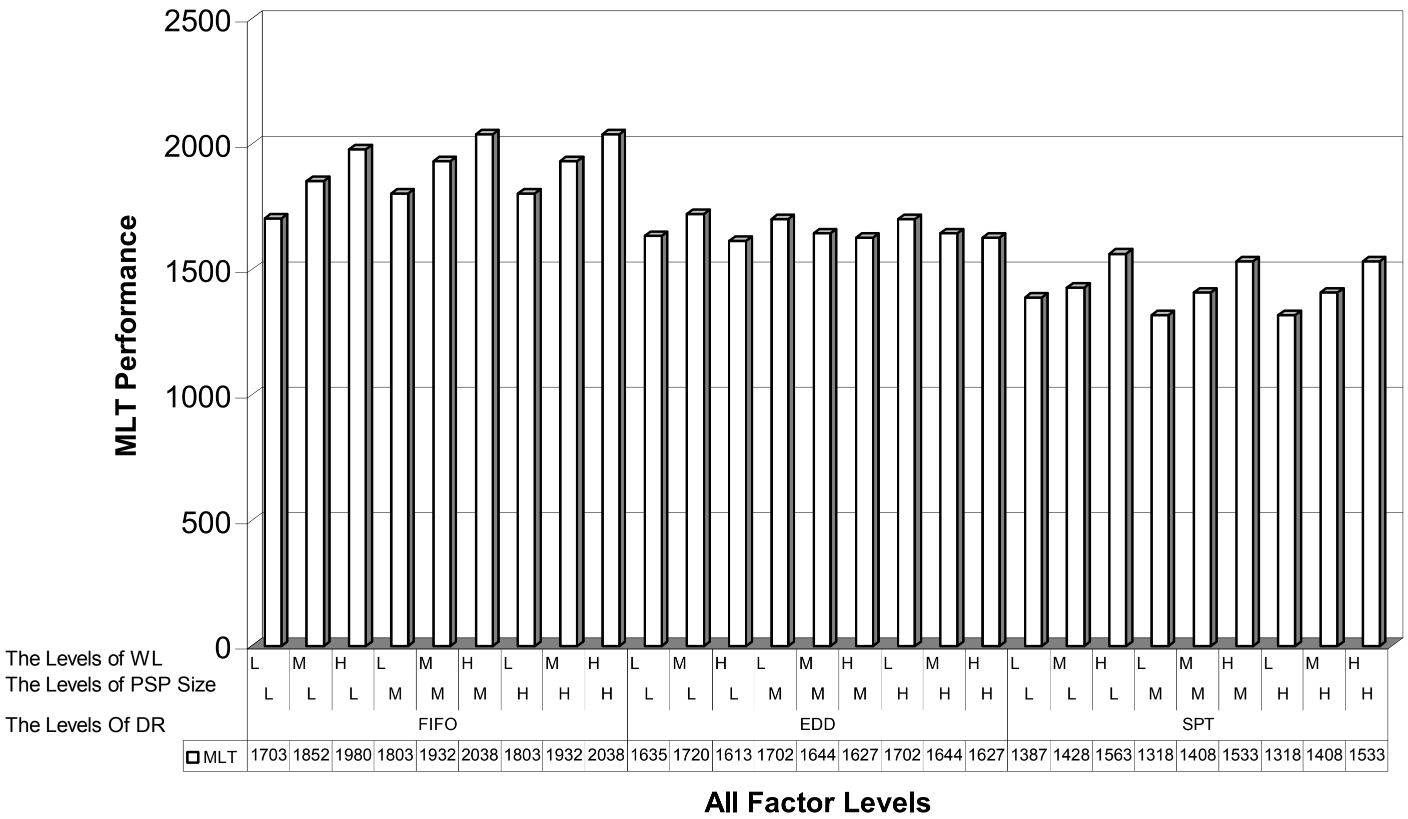


Figure A.29. MLT Performance with WCWT at low DF

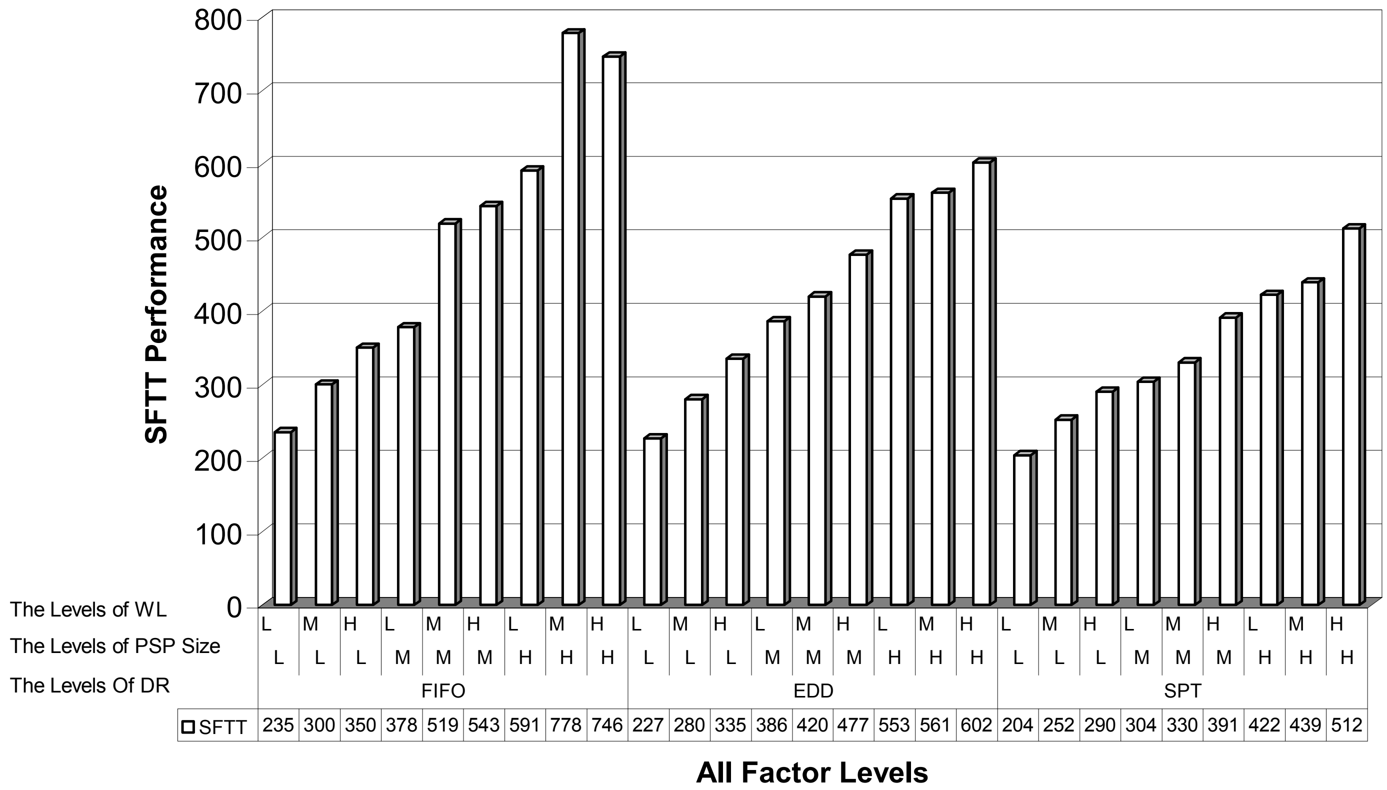
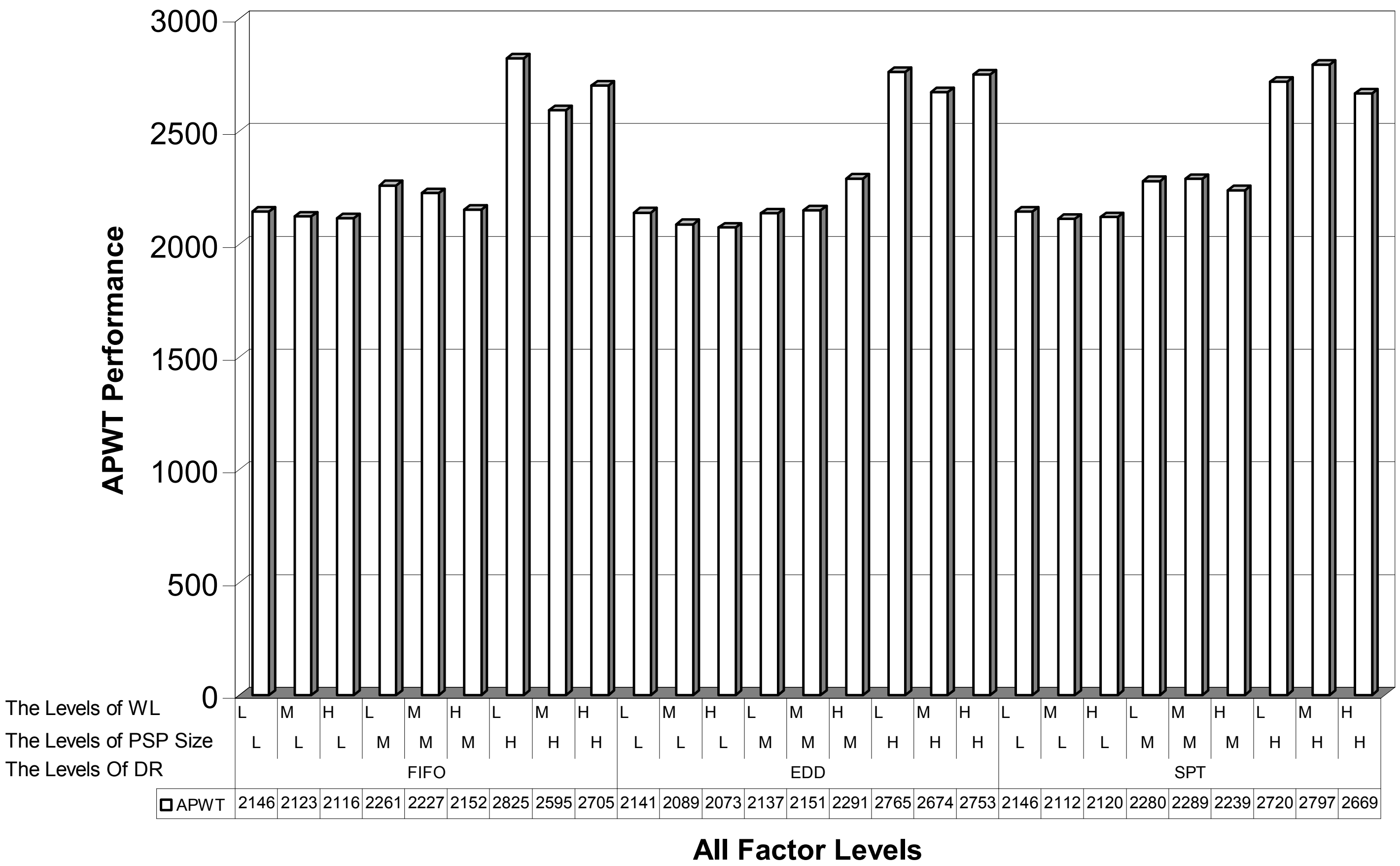
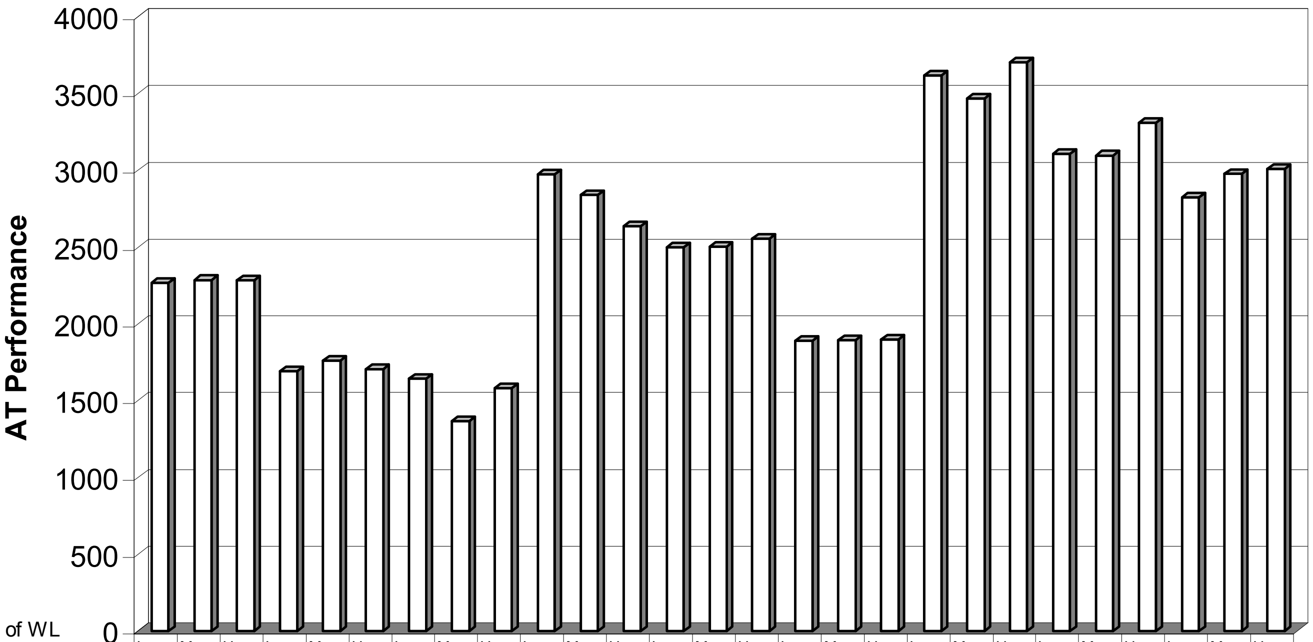


Figure A.30. SFTT Performance with WCWT at low DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
APWT	2146	2123	2116	2261	2227	2152	2825	2595	2705	2141	2089	2073	2137	2151	2291	2765	2674	2753	2146	2112	2120	2280	2289	2239	2720	2797	2669

Figure A.31. APWT Performance with WCWT at low DF



	FIFO									EDD									SPT								
The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
AT	2264	2284	2281	1690	1758	1704	1641	1366	1581	2972	2838	2633	2497	2502	2553	1889	1894	1896	3616	3466	3700	3104	3095	3309	2821	2976	3009

The Levels Of DR: FIFO, EDD, SPT

Figure A.32. AT Performance with WCWT at low DF

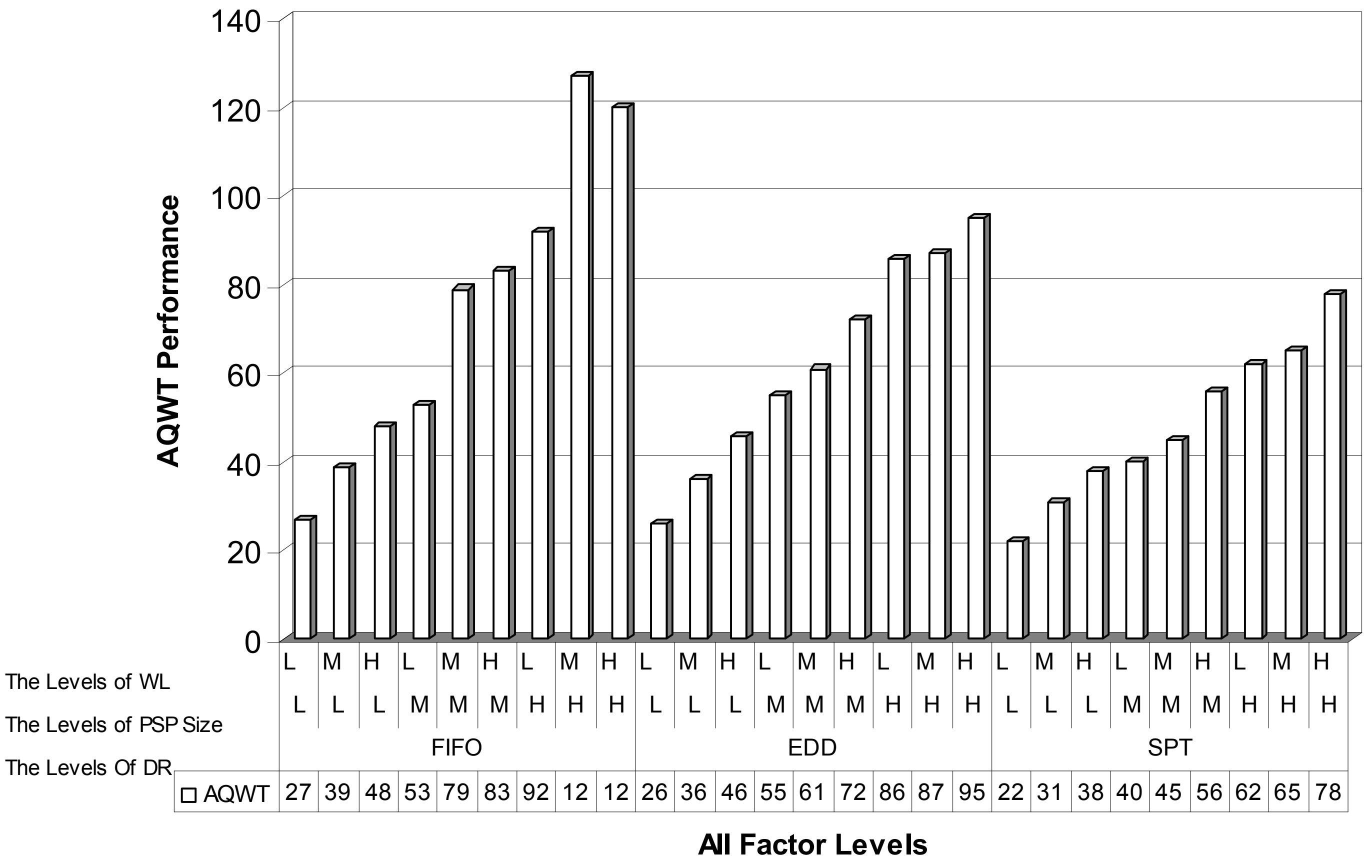
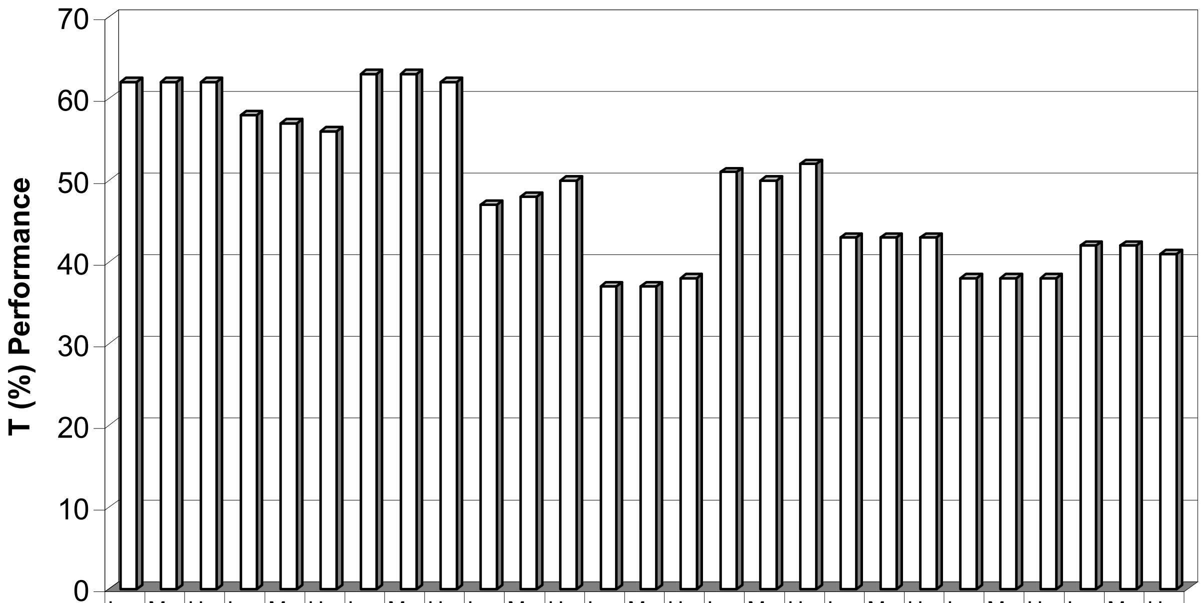


Figure A.33. AQWT Performance with WCWT at low DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
T (%)	62	62	62	58	57	56	63	63	62	47	48	50	37	37	38	51	50	52	43	43	43	38	38	38	42	42	41

Figure A.34. T (%) Performance with WCWT at low DF

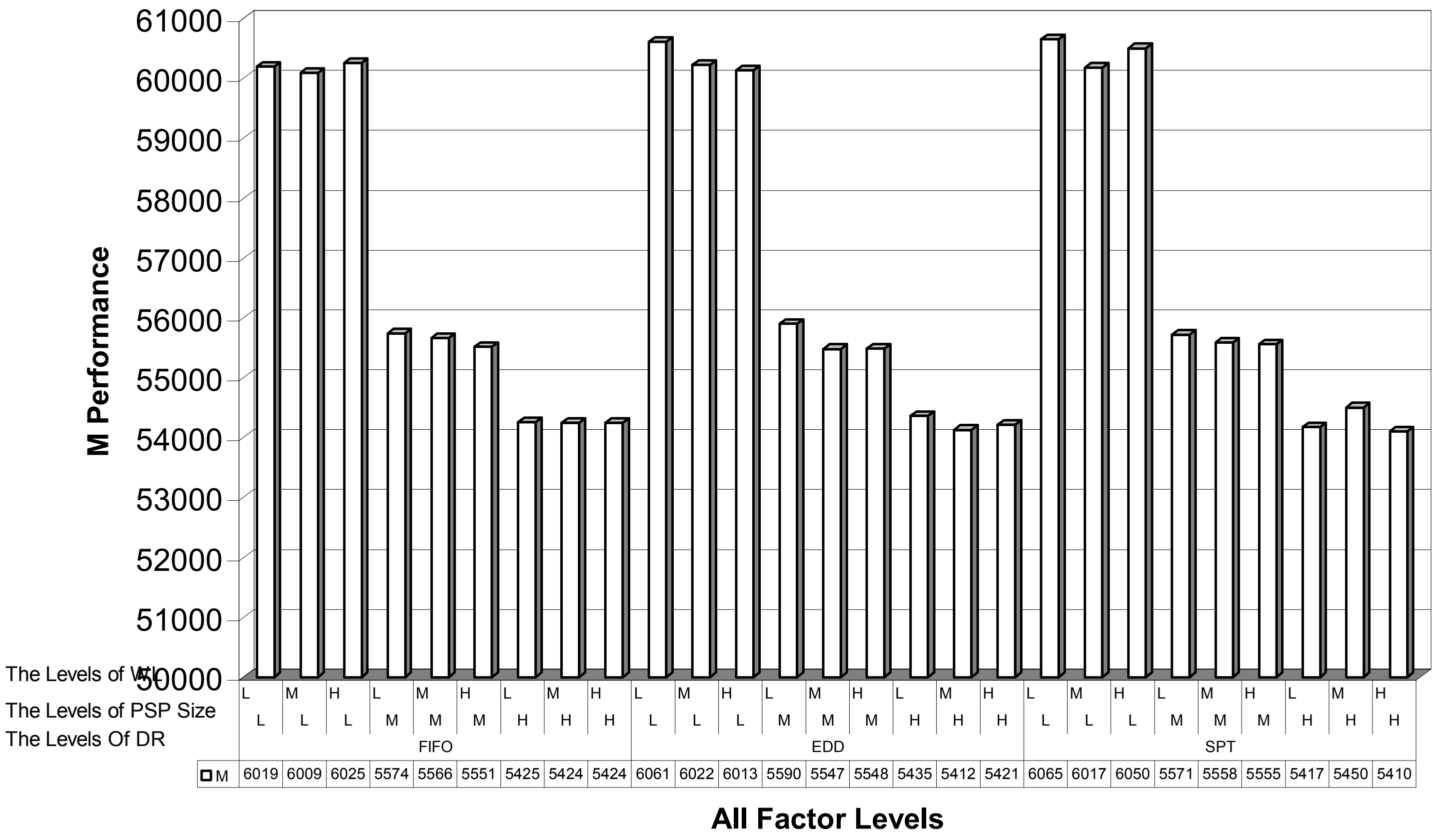


Figure A.35. M Performance with WCWT at low DF

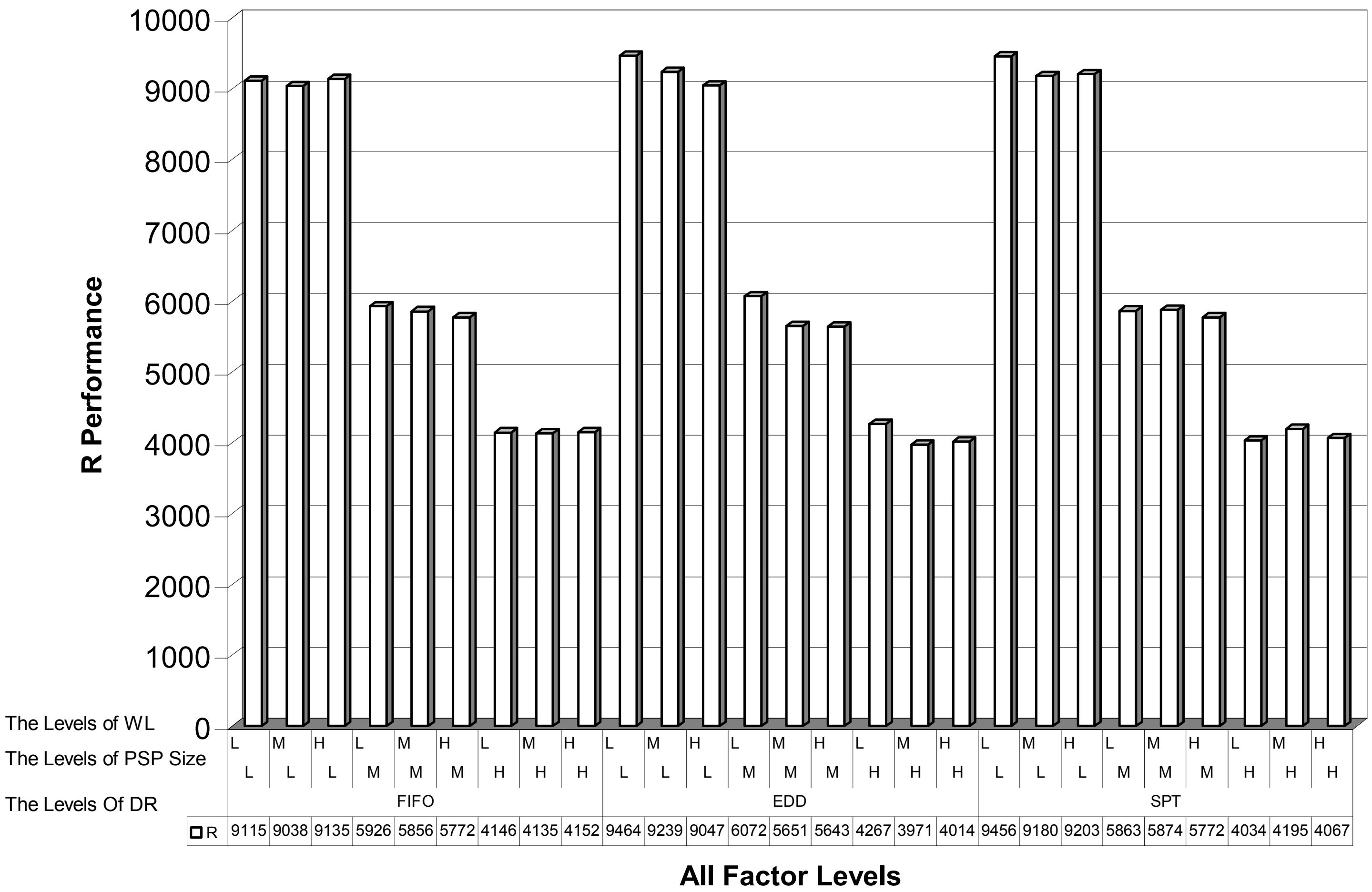


Figure A.36. R Performance with WCWT at low DF

Table A.10. Measures of main Performances with WCWT at low DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
0	WCWT	FIFO	1000	50	22	07	2361	235	2146	1347	5508	2264	-176	27	62	38	60196	9115
			1000	100	21	07	2394	300	2123	1345	5527	2284	-171	39	62	38	60090	9038
			1000	150	20	07	2435	350	2116	1345	5570	2281	-165	48	62	38	60257	9135
			2000	50	20	03	2623	378	2261	749	5028	1690	-526	53	58	42	55740	5926
			2000	100	19	03	2717	519	2227	790	5306	1758	-505	79	57	43	55664	5856
			2000	150	18	03	2668	543	2152	748	5060	1704	-474	83	56	44	55519	5772
			3000	50	18	07	3380	591	2825	917	3997	1641	-323	92	63	37	54255	4146
			3000	100	17	06	3334	778	2595	729	2921	1366	-338	127	63	37	54245	4135
			3000	150	17	07	3402	746	2705	872	3716	1581	-296	120	62	38	54249	4152
		EDD	1000	50	41	-16	2355	227	2141	1335	5562	2972	-142	26	47	53	60610	9464
			1000	100	46	-20	2354	280	2089	1286	5387	2838	-148	36	48	52	60228	9239
			1000	150	47	-21	2393	335	2073	1228	5128	2633	-157	46	50	50	60132	9047
			2000	50	62	-43	2507	386	2137	676	5083	2497	-394	55	37	63	55904	6072
			2000	100	71	-51	2554	420	2151	698	5090	2502	-374	61	37	63	55478	5651
			2000	150	76	-56	2744	477	2291	746	5061	2553	-378	72	38	62	55481	5643
			3000	50	50	-24	3281	553	2765	806	3705	1889	-300	86	51	49	54358	4267
			3000	100	56	-31	3180	561	2674	806	3721	1894	-267	87	50	50	54127	3971
			3000	150	56	-29	3285	602	2753	864	3778	1896	-244	95	52	48	54215	4014
		SPT	1000	50	124	-94	2333	204	2146	1357	6146	3616	-366	22	43	57	60653	9456
			1000	100	178	-148	2346	252	2112	1172	5944	3466	-535	31	43	57	60179	9180
			1000	150	216	-186	2387	290	2120	1249	6363	3700	-626	38	43	57	60501	9203
			2000	50	202	-176	2568	304	2280	686	6158	3104	-787	40	38	62	55718	5863
			2000	100	251	-226	2597	330	2289	582	6296	3095	-954	45	38	62	55586	5874
			2000	150	308	-282	2605	391	2239	542	6658	3309	-1119	56	38	62	55555	5772
			3000	50	301	-273	3118	422	2720	671	5460	2821	-898	62	42	58	54177	4034
			3000	100	328	-299	3208	439	2797	640	5700	2976	-1030	65	42	58	54502	4195
			3000	150	403	-375	3147	512	2669	537	5947	3009	-1200	78	41	59	54101	4067

A.7. The effect of the levels of WL with WCWT on other predetermined performance measures at intermediate DF

In Table A.11, the resulting measures of other shop performances with WCWT OR mechanism at intermdiate DF is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed below.

MAPE: From Figure A.37., it is seen that the MAPE performance of the shop is significantly affected by different levels of DRs and WL. PSP size factor has no significant effect on the MAPE performance. As the levels of WL increases the MAPE performance improves for FIFO DR. For other DRs it is just the opposite. So, for both EDD and SPT DRs the best MAPE performance is attained at low WL. Let's focus on FIFO DR. In this case, it is apparent that the higher levels of WL provide better MAPE performance. It seems opposed to our suggestion up to here that the low level of WL improves the MAPE and other predetermined performance measures. But, this is not just the case. For example, consider the first factor combination where the level of PSP size is 1000, WL is 50. In this case the value of average MAPE and MLT value is 19% and 1703, respectively. Also, consider the second factor combination where the level of PSP size is 1000, WL is 100. In this case the value of average MAPE and MLT value is 16% and 1852, respectively. If we prefer the higher levels of WL for the sake of an 3% increase on due date reliability performance we will face up to a 12,5% decrease on delivery speed which is unreasonable. The reasonable choice should be the first factor combination where the level of WL is 50. So, there is no evidence against setting the level of WL to its low level in terms of MAPE performance measure.

MLT: The levels of WL and DRs have significant effect on the MLT performance. For FIFO and SPT DRs, the best MLT performance is attained at low WL regardless of PSP size. However, this is just the opposite for EDD DR. In the case of EDD DR with high level of WL, the decrease in MLT values is outweighed by the increase in MAPE values which makes the choice of these levels inevitable. So, there is no evidence against setting the level of WL to its low level in terms of MLT performance measure.

SFTT: WL and DR have significant effect on the SFTT performance of the shop. PSP size have no significant effect on the SFTT performance of the shop. From Figure A.39., low level of WL improves the SFTT performance. So there is no evidence against setting the level of WL to its low level in terms of SFTT performance measure.

APWT: The levels of WL and DRs have significant effect on APWT performance. As the level of WL increases the APWT performance improves. But, note that there is a trade-off between APWT performance and SFTT performance of the shop. That is, changing from low to higher WL improves the APWT performance but deteriorates the SFTT performance. In this case, the MLT performance, which is the summation of APWT and SFTT performances of the shop, should be evaluated to assist determining the appropriate level of WL. As mentioned above, there is no evidence against setting WL to its low level in terms of MLT performance and APWT performance as well.

AT: From Figure A.41., the AT performance of the shop affected by all factor combinations. For FIFO DR the levels of the WL have no significant effect on the AT performance at low PSP size. For higher levels of PSP size the level of WL effects the AT performance significantly. In this case, as the level of WL increases the AT performance of the shop improves. For EDD DR, at low level of PSP size intermediate WL improves the AT performance whereas higher PSP sizes at high WL improves it. But, note that the amount of improvement gained by using high WL instead of low WL is negligible. For SPT DR, the levels of WL have no significant effect on AT performance. So, there is no evidence against setting WL to its low level in terms of AT performance measure.

AQWT: The levels of WL and DRs have significant effect on the AQWT performance of the shop. As the level of WL decreases the AQWT performance of the shop improves. So, there is no evidence against setting the level of WL to its low level in terms of AQWT performance measure.

T (%): The T (%) performance is mainly affected by WL and DR. For, FIFO DR it is not affected by neither the levels of PSP size nor the levels of WL. But, for EDD and SPT DRs it is mainly affected by the level of the WL. For SPT DR, the best T (%) performance is attained at low WL. But, this is not the case for EDD DR. Note that in this case the worst T(%) performance is attained at low WL. But, decrease in the T(%) values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL inevitable for this case. So there is no evidence against setting the level of WL to its low level in terms of T (%) performance measure.

M: The M performance of the shop affected by all factors. For FIFO and SPT DR, the low level of WL improves the M performance regardless of the levels of PSP size. For the EDD DR, the best M performance is attained at either high or low WL. However, note that there is no significant difference between M values with different levels of WL for EDD DR. So there is no evidence against setting the level of WL to its low level in terms of M performance measure.

R: All factors have significant effect on R performance of the shop. Rejection of orders occurs only at low PSP size with each DRs and WL. Note that the average total number of rejected orders is negligible even for the worst case. So, there is no evidence against setting the level of WL to its lowest level in terms of R performance measure.

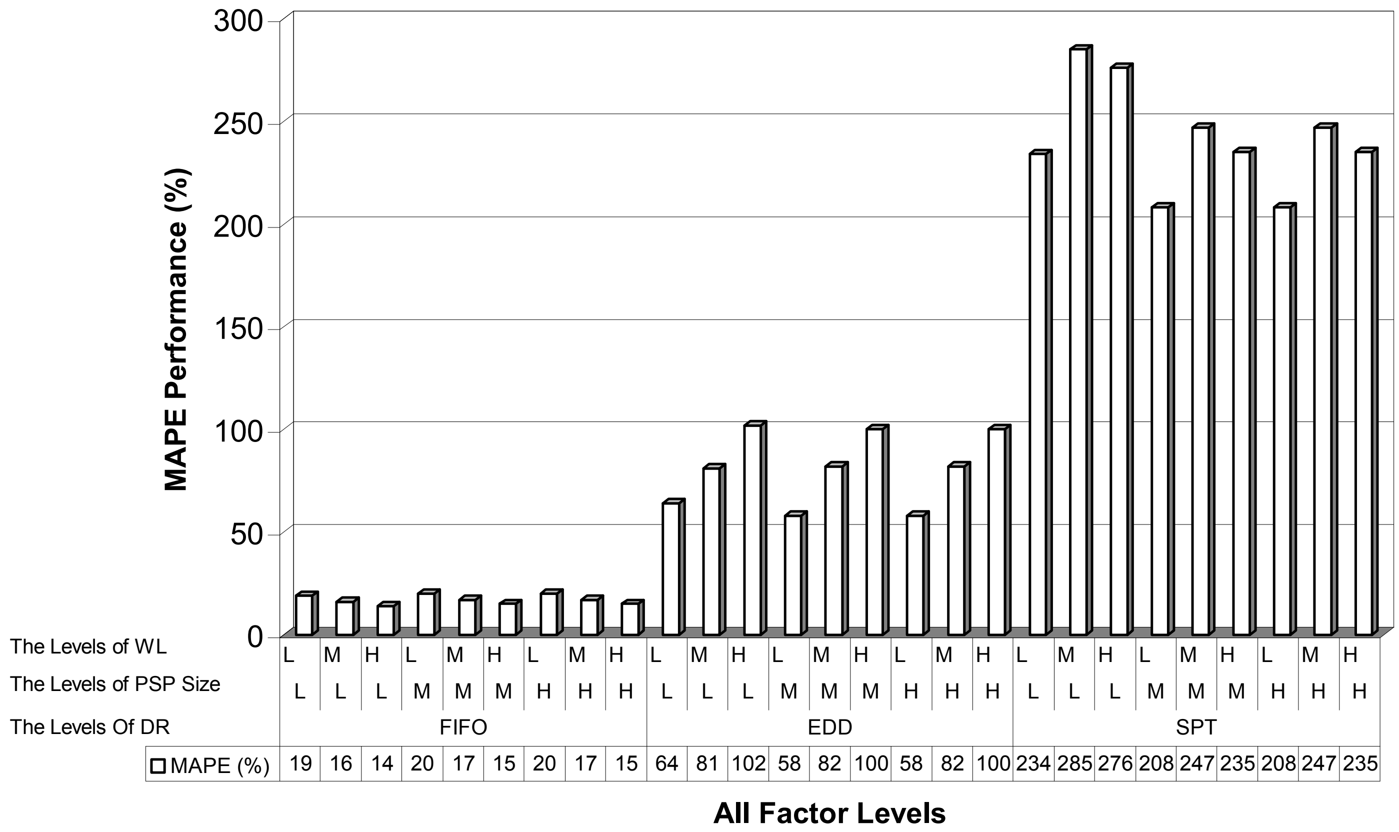
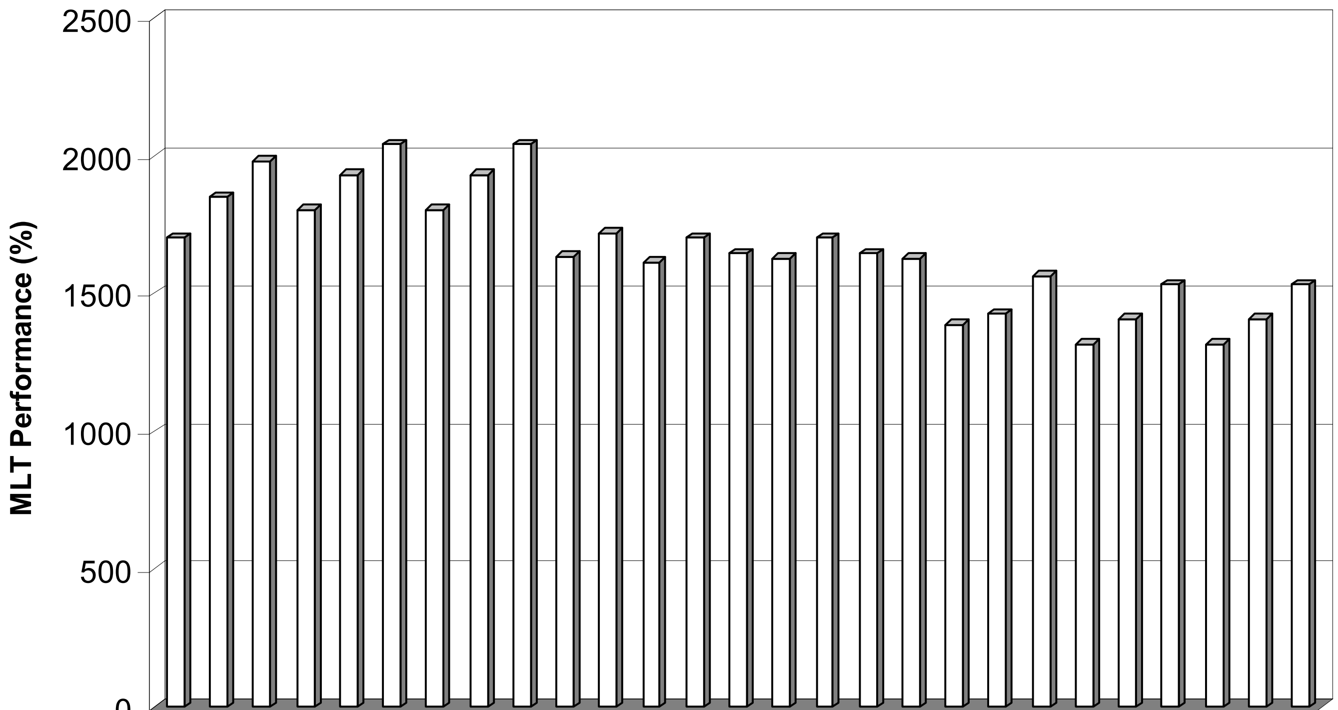


Figure A.37. MAPE Performance with WCWT at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
MLT	1703	1852	1980	1803	1932	2038	1803	1932	2038	1635	1720	1613	1702	1644	1627	1702	1644	1627	1387	1428	1563	1318	1408	1533	1318	1408	1533

Figure A.38. MLT Performance with WCWT at intermediate DF

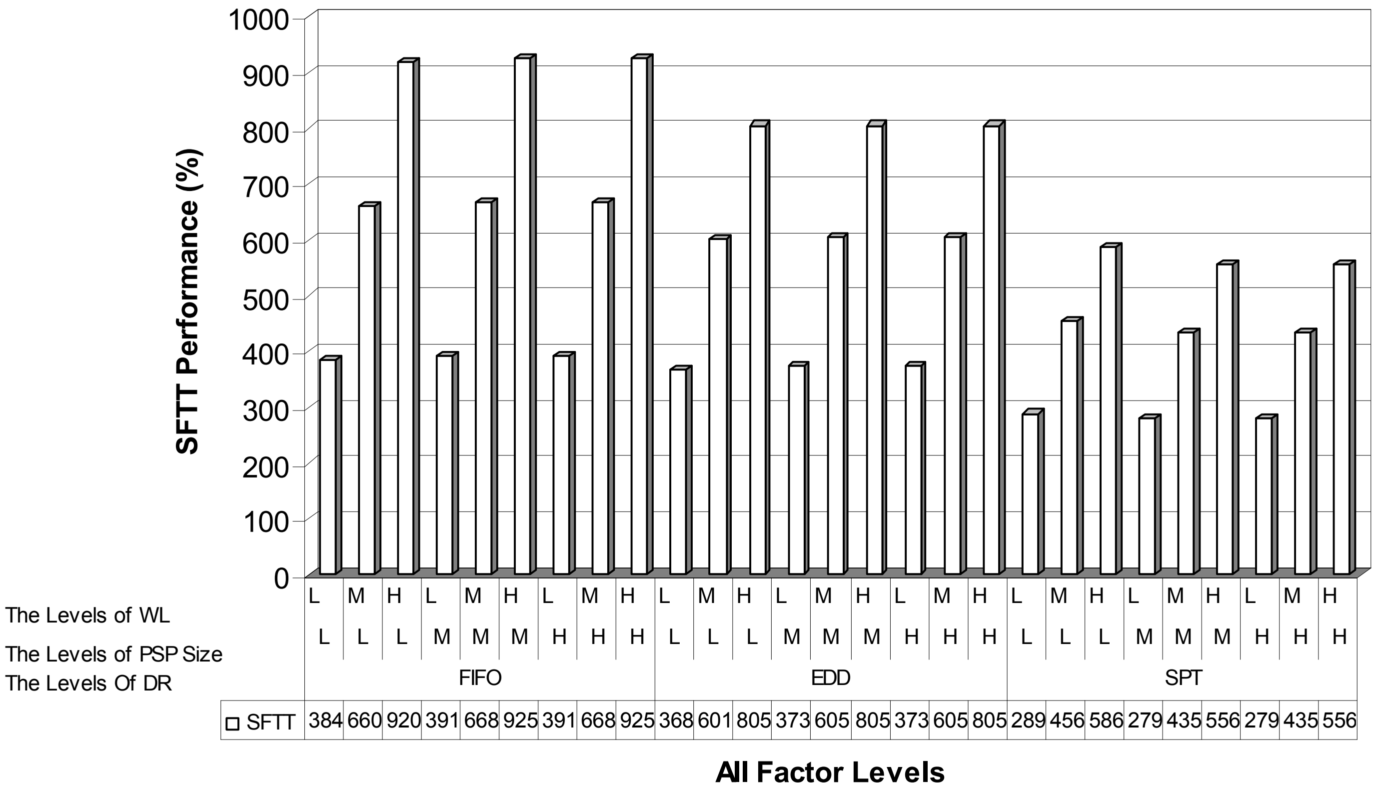


Figure A.39. SFTT Performance with WCWT at intermediate DF

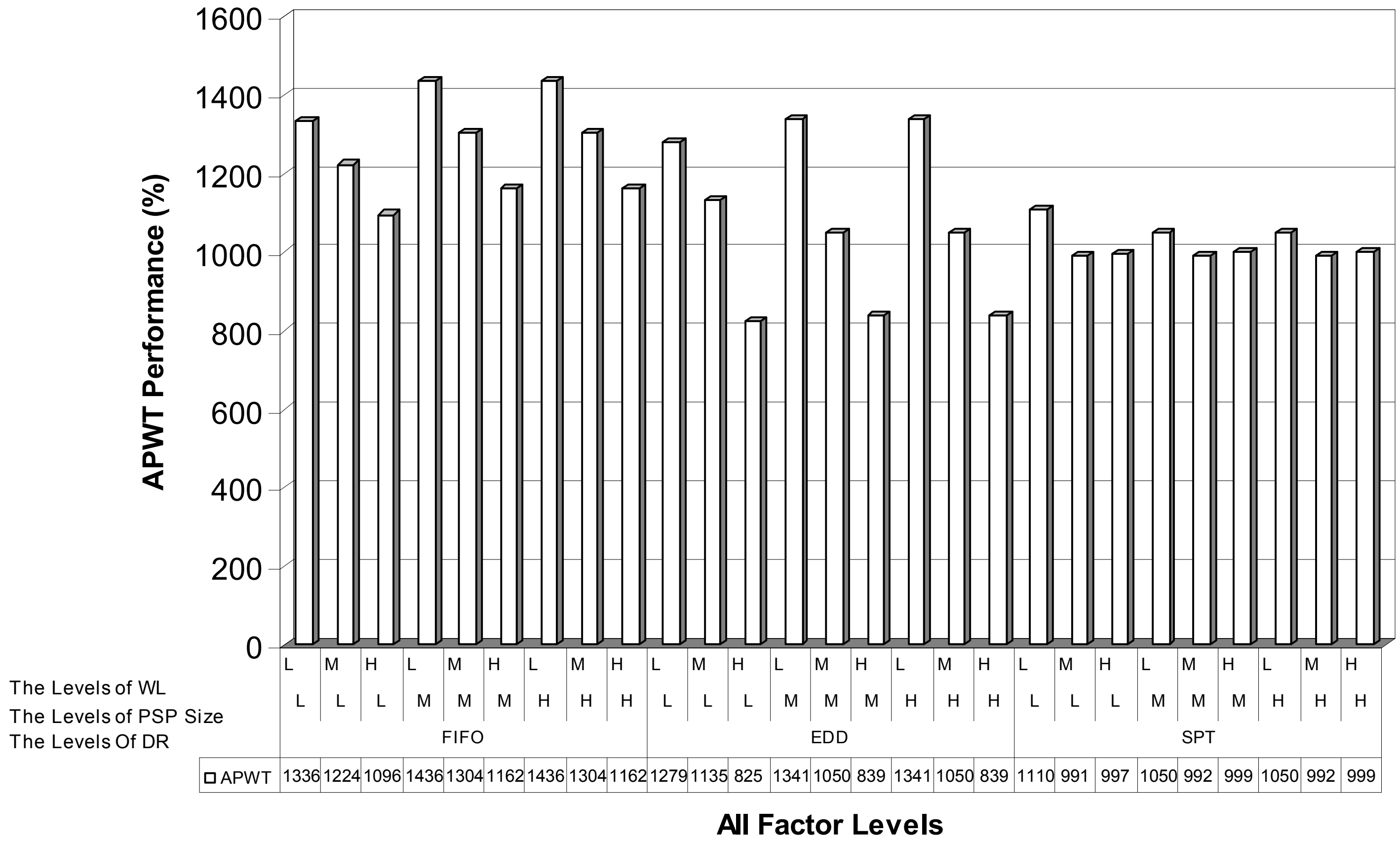


Figure A.40. APWT Performance with WCWT at intermediate DF

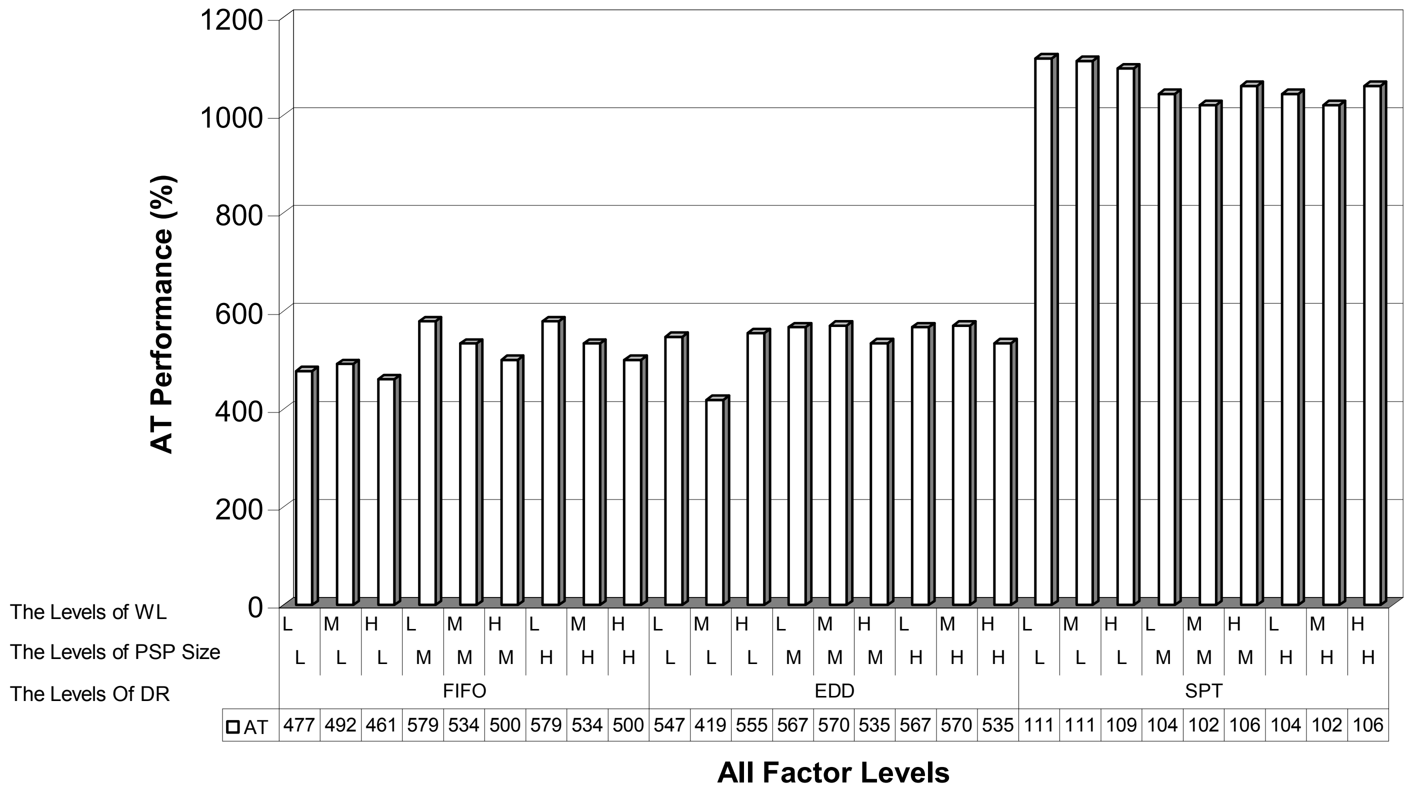
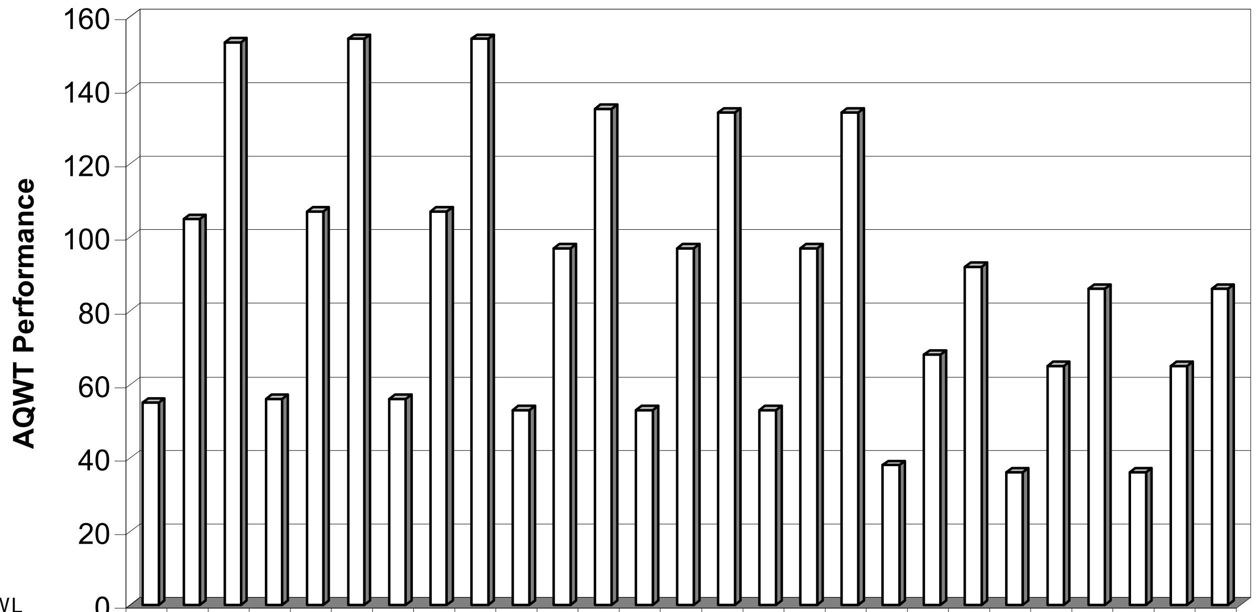


Figure A.41. AT Performance with WCWT at intermediate DF



The Levels of WL	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
The Levels of PSP Size	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H	L	L	L	M	M	M	H	H	H
The Levels Of DR	FIFO									EDD									SPT								
AQWT	55	105	153	56	107	154	56	107	154	53	97	135	53	97	134	53	97	134	38	68	92	36	65	86	36	65	86

Figure A.42. AQWT Performance with WCWT at intermediate DF

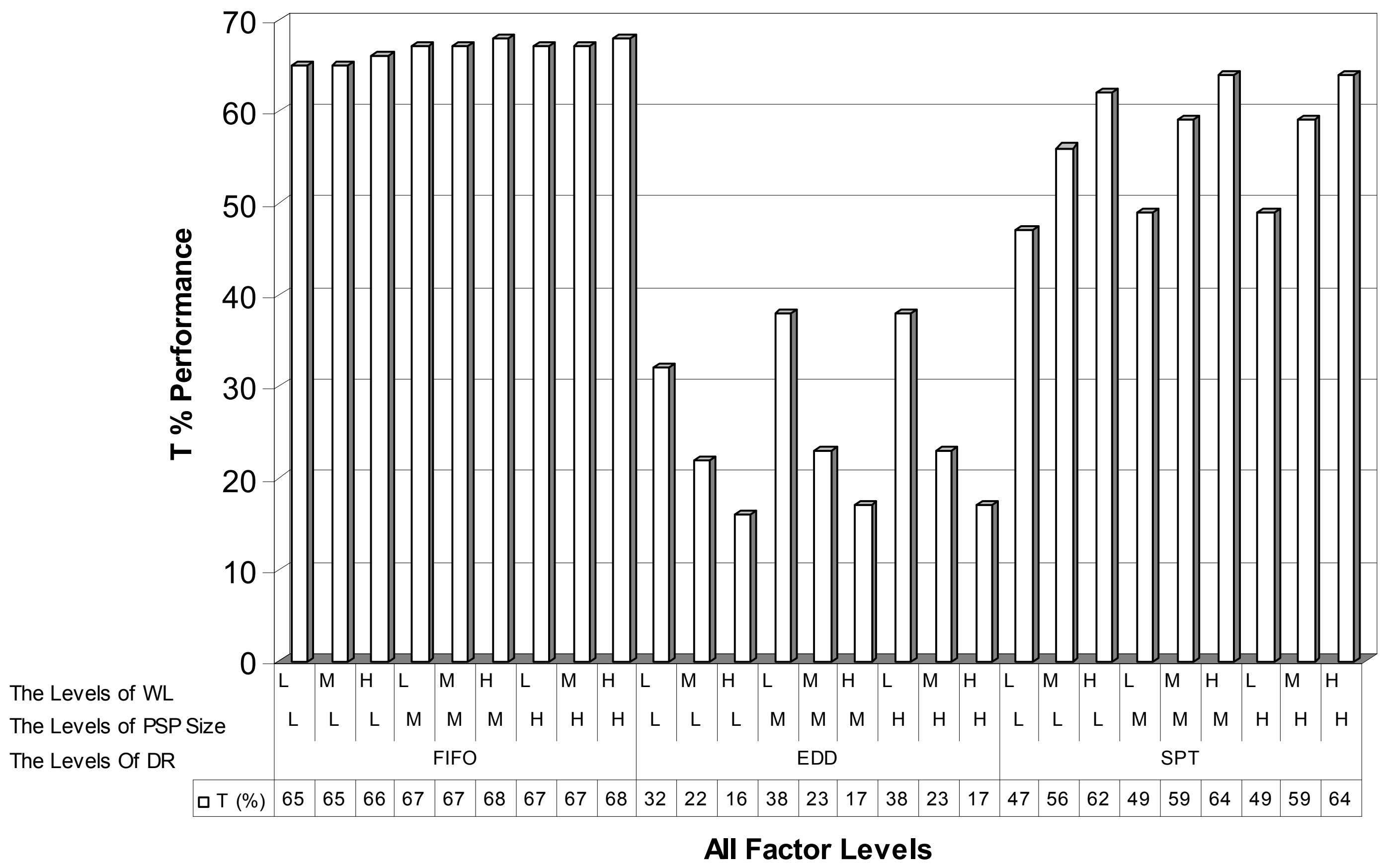


Figure A.43. T (%) Performance with WCWT at intermediate DF

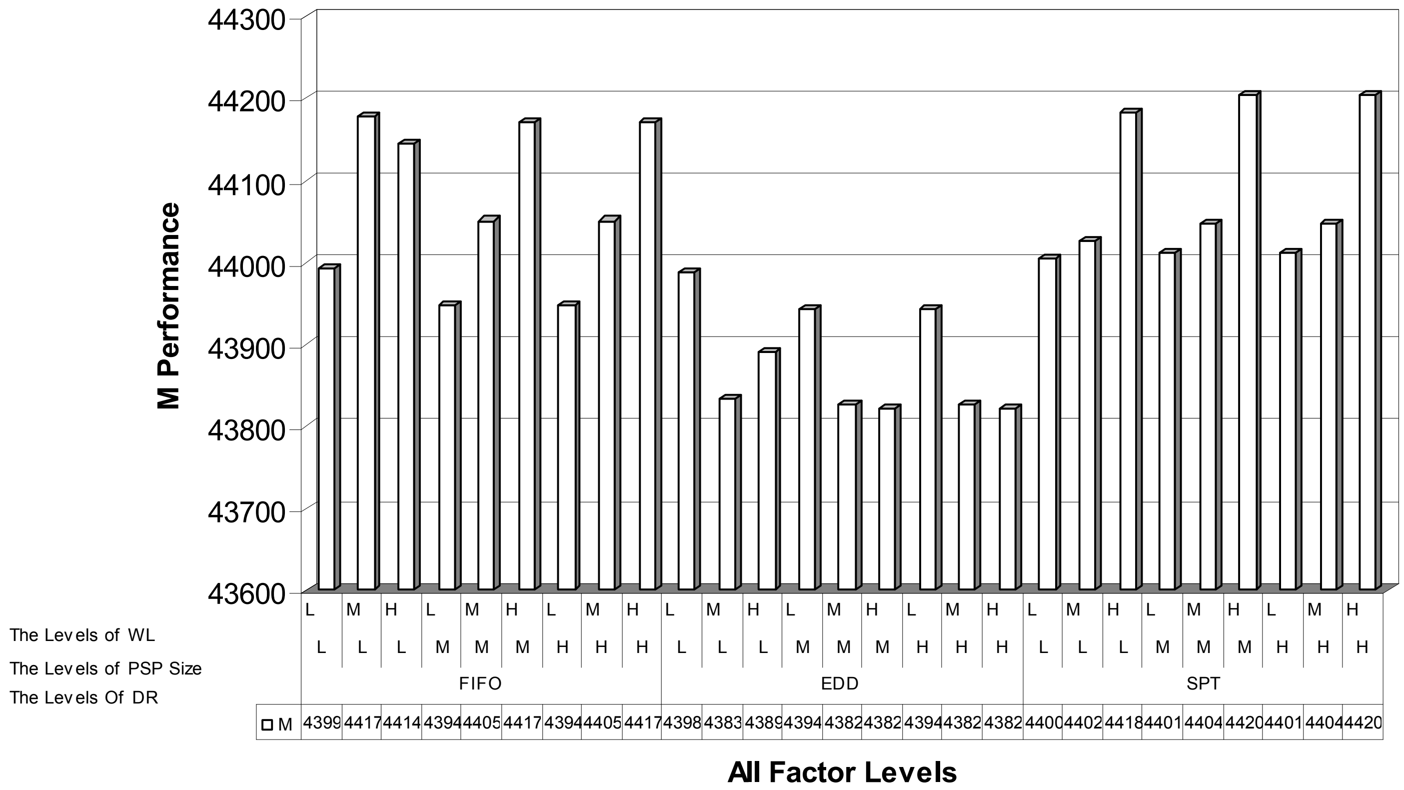


Figure A.44. M Performance with WCWT at intermediate DF

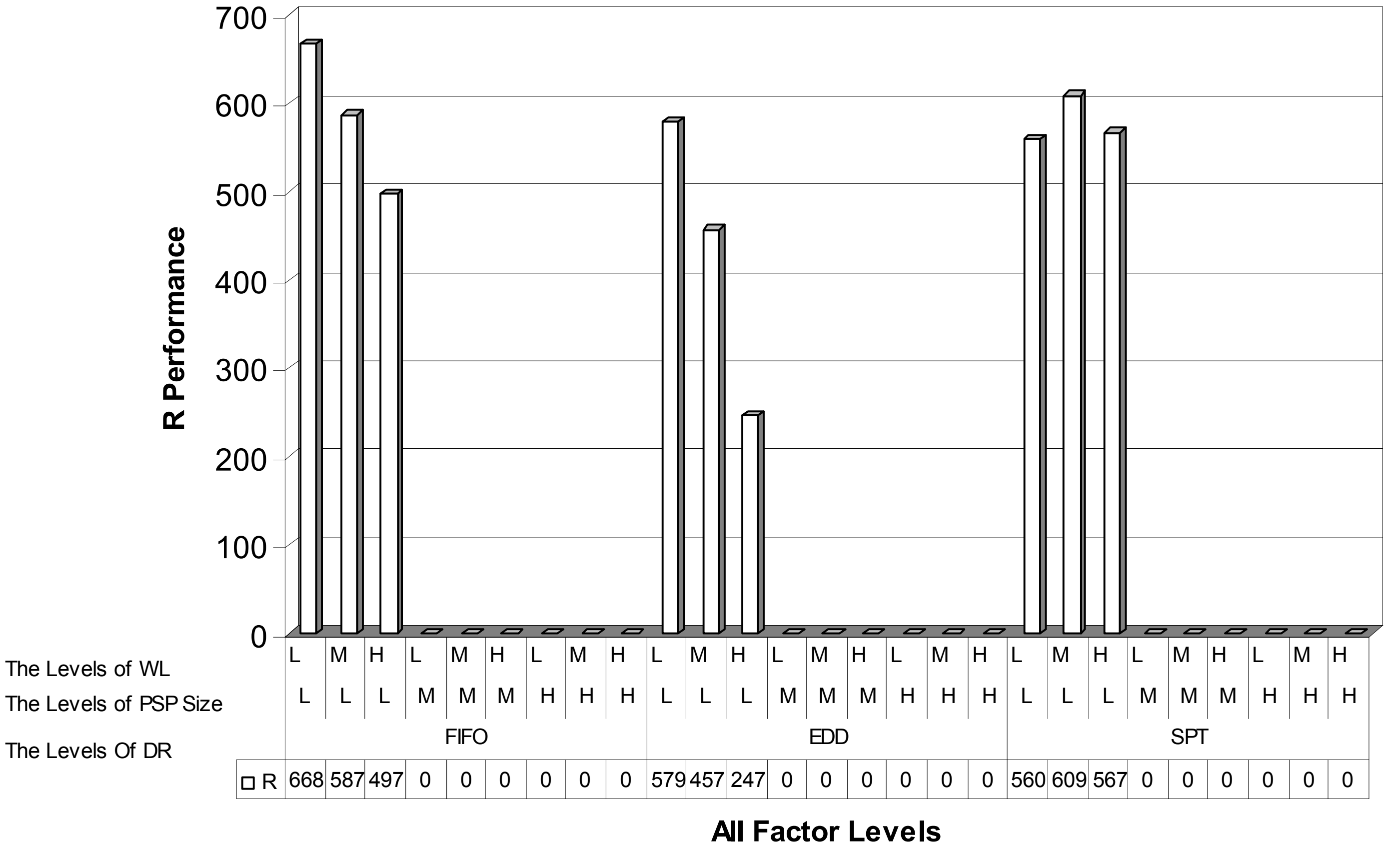


Figure A.45. R Performance with WCWT at intermediate DF

Table A.11. Measures of main Performances with WCWT at intermediate DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
1	WCWT	FIFO	1000	50	19	05	1703	384	1336	270	688	477	-107	55	65	35	43992	668
			1000	100	16	06	1852	660	1224	275	717	492	-124	105	65	35	44177	587
			1000	150	14	06	1980	920	1096	259	692	461	-128	153	66	34	44144	497
			2000	50	20	07	1803	391	1436	359	818	579	-93	56	67	33	43948	0
			2000	100	17	07	1932	668	1304	325	759	534	-107	107	67	33	44051	0
			2000	150	15	07	2038	925	1162	306	740	500	-108	154	68	32	44170	0
			3000	50	20	07	1803	391	1436	359	818	579	-93	56	67	33	43948	0
			3000	100	17	07	1932	668	1304	325	759	534	-107	107	67	33	44051	0
			3000	150	15	07	2038	925	1162	306	740	500	-108	154	68	32	44170	0
		EDD	1000	50	64	-53	1635	368	1279	58	583	547	-175	53	32	68	43987	579
			1000	100	81	-73	1720	601	1135	-82	402	419	-222	97	22	78	43834	457
			1000	150	102	-96	1613	805	825	-133	464	555	-257	135	16	84	43891	247
			2000	50	58	-45	1702	373	1341	114	671	567	-152	53	38	62	43943	0
			2000	100	82	-73	1644	605	1050	-33	534	570	-208	97	23	77	43827	0
			2000	150	100	-94	1627	805	839	-121	459	535	-251	134	17	83	43822	0
			3000	50	58	-45	1702	373	1341	114	671	567	-152	53	38	62	43943	0
			3000	100	82	-73	1644	605	1050	-33	534	570	-208	97	23	77	43827	0
			3000	150	100	-94	1627	805	839	-121	459	535	-251	134	17	83	43822	0
		SPT	1000	50	234	-199	1387	289	1110	140	3096	1115	-723	38	47	53	44005	560
			1000	100	285	-238	1428	456	991	111	3826	1110	-1141	68	56	44	44027	609
			1000	150	276	-218	1563	586	997	191	3925	1095	-1292	92	62	38	44183	567
			2000	50	208	-172	1318	279	1050	161	2848	1043	-674	36	49	51	44012	0
			2000	100	247	-198	1408	435	992	176	3415	1020	-1029	65	59	41	44048	0
			2000	150	235	-176	1533	556	999	250	3482	1060	-1176	86	64	36	44205	0
			3000	50	208	-172	1318	279	1050	161	2848	1043	-674	36	49	51	44012	0
			3000	100	247	-198	1408	435	992	176	3415	1020	-1029	65	59	41	44048	0
			3000	150	235	-176	1533	556	999	250	3482	1060	-1176	86	64	36	44205	0

A.8. The effect of the levels of WL with WCWT on other predetermined performance measures at high DF

In Table A.12, the resulting measures of other shop performances with WCWT OR mechanism at high DF is tabulated. Among these results mainly MAPE, MLT, SFTT, APWT, AT, %T, M, and R performance measures will be discussed below.

MAPE: From Figure A.46., it is seen that the MAPE performance of the shop is significantly affected by different levels of DRs. For FIFO DRs the levels of WL have no significant effect on MAPE performance. For EDD DR, the best MAPE performance is attained at low level of WL. For SPT DR, the levels of WL significantly affect the MAPE performance. But, even the best MAPE performance obtained by using SPT DR is inevitable. So, there is no evidence against setting the level of WL to its low level in terms of MAPE performance measure.

MLT: All factors have significant effect on the MLT performance. For FIFO and SPT DRs, the best MLT performance is attained at low WL regardless of the level of PSP size. But, this is not the case for EDD DR. In this case, MLT performance deteriorates with the low level of WL. But, the decrease in MLT values is outweighed by the increase in MAPE values which makes the choice of higher level of WL inevitable. So, there is no evidence against setting the level of WL to its lowest level in terms of MLT performance measure.

SFTT: The levels of WL and DRs have significant effect on the SFTT performance of the shop. From Figure A.48., it is apparent that the best SFTT performance is attained at low WL. So, there is no evidence against setting the level of WL to its low level in terms of SFTT performance measure.

APWT: WL and DRs have significant effect on APWT performance. Changing from low to higher WL improves the APWT performance. But, note that there is a trade-off between APWT performance and SFTT performance of the shop. That is, as the level of WL increases the APWT performance improves whereas the SFTT performance deteriorates. In this case, the MLT performance, which is the summation of APWT and SFTT performances of the shop, should be evaluated to assist determining the appropriate level of WL. As mentioned above, there is no evidence against setting the level of WL to its low level in terms of MLT performance and APWT performance as well.

AT: From Figure A.50. it is apparent that AT performance of the shop affected by all factors. For FIFO DR the levels of the WL have no significant effect on the AT performance regardless of PSP size. For EDD dispatching rule, the low level of WL worsens AT performance regardless of PSP size. However, note that the amount of AT difference between low WL and high WL is 108 time units at low PSP size and is negligible . For SPT DR, the levels of WL have significant effect on AT performance. In this case, the best AT performance is attained at intermediate level of WL. But, even the best AT performance is inevitable in this case. Determining the effect of the levels of WL on AT performance is somewhat cumbersome. But, there is no evidence against setting the level of WL to its low level in terms of AT performance measure.

AQWT: The levels of WL and DRs have significant effect on the AQWT performance of the shop. The best AQWT performance is attained at low WL regardless of other factors. So, there is no evidence against setting the level of WL to its low level in terms of AQWT performance measure.

T (%): The T (%) performance is significantly affected by the levels of DRs and WL. For, FIFO DR it is not affected neither the levels of PSP size nor the levels of WL factors. But, for EDD and SPT DRs it is mainly affected by the level of the WL. For SPT DR, selecting the low levels of WL results in better T(%) performance of the shop. But, this is not the case for EDD DR. Note that in this case as the levels of WL increases T(%) performance improves. But, decrease in the T(%) values is outweighed by the increase in MAPE values which makes the choice of higher levels of WL inevitable for this case. So there is no evidence against setting the level of WL to its low level in terms of T (%) performance measure.

M: The M performance of the shop is only affected by the levels WL and DRs. For FIFO and SPT DR, the low level of WL improves the M performance regardless of PSP size. For the EDD DR the M performance of the shop worsens at low WL. However, note that there is no significant difference among M values with each level of WL for EDD DR. So there is no evidence for against the level of WL to its low level in terms of M performance measure.

R: All factors have significant effect on R performance. Rejection of orders occurs only at low PSP size with each DRs and WL. As the level of WL increases the R performance of the shop improves. But, note that the average total number of rejected orders is negligible even for the worst case. So, there is no evidence against setting the level of WL to its low level in terms of R performance measure.

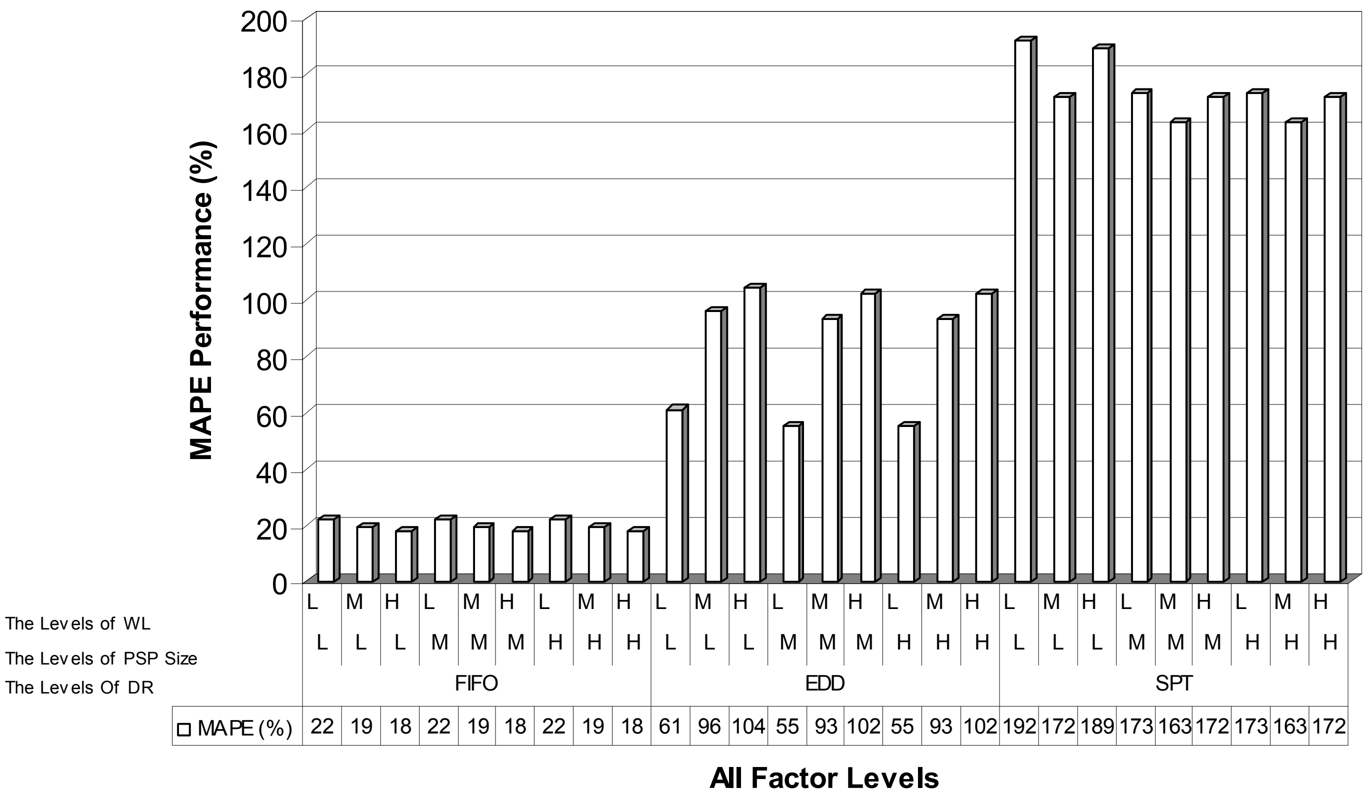


Figure A.46. MAPE Performance with WCWT at high DF

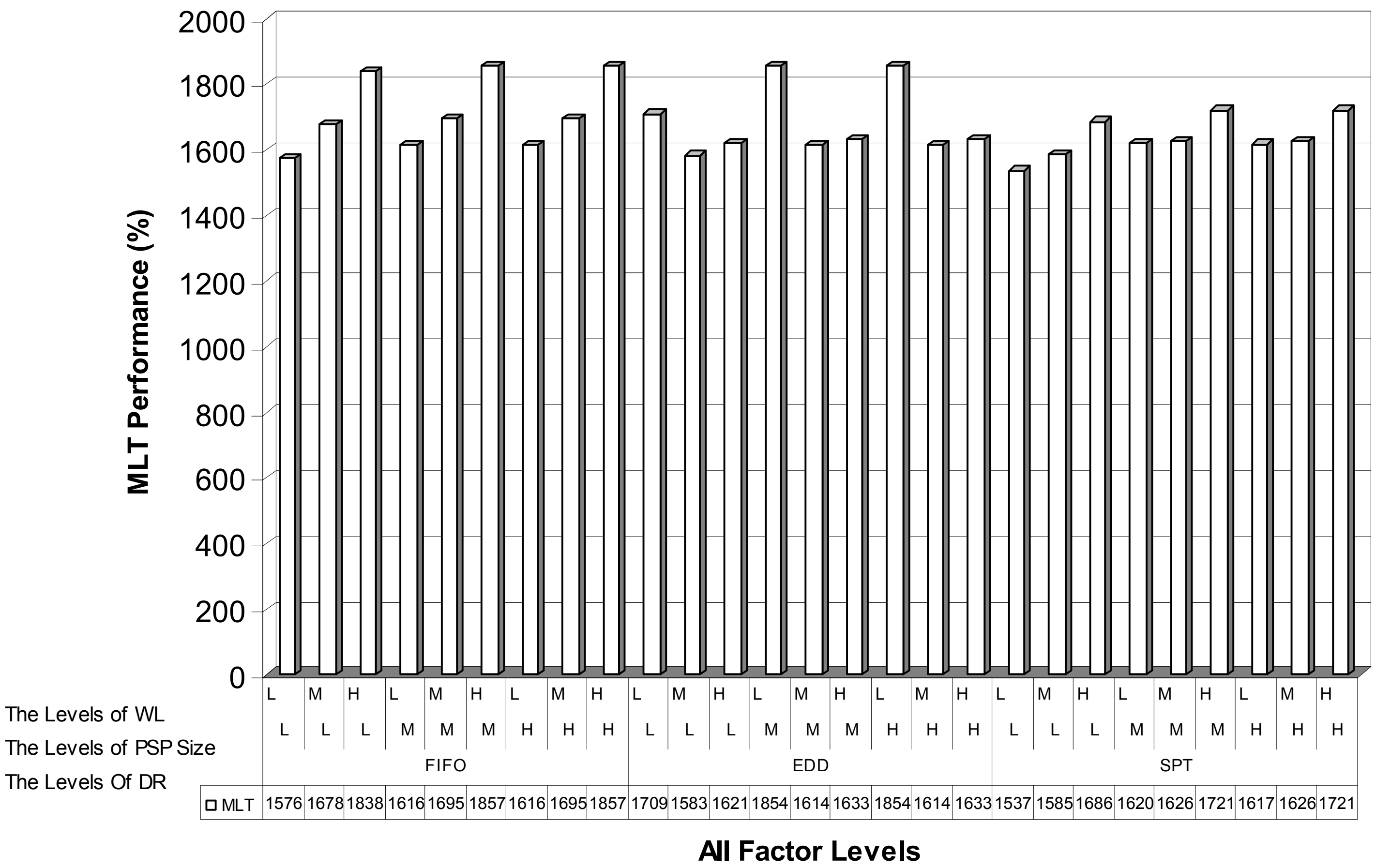


Figure A.47. MLT Performance with WCWT at high DF

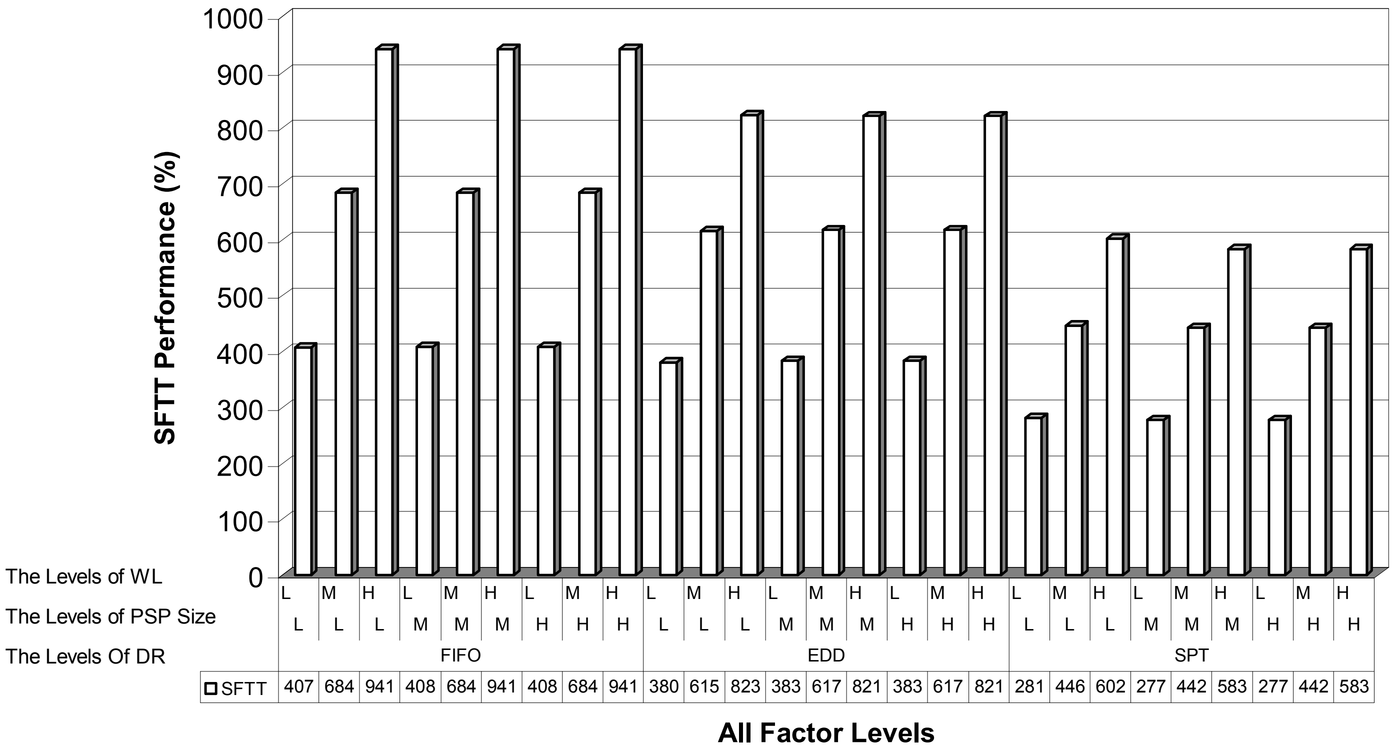


Figure A.48. SFTT Performance with WCWT at high DF

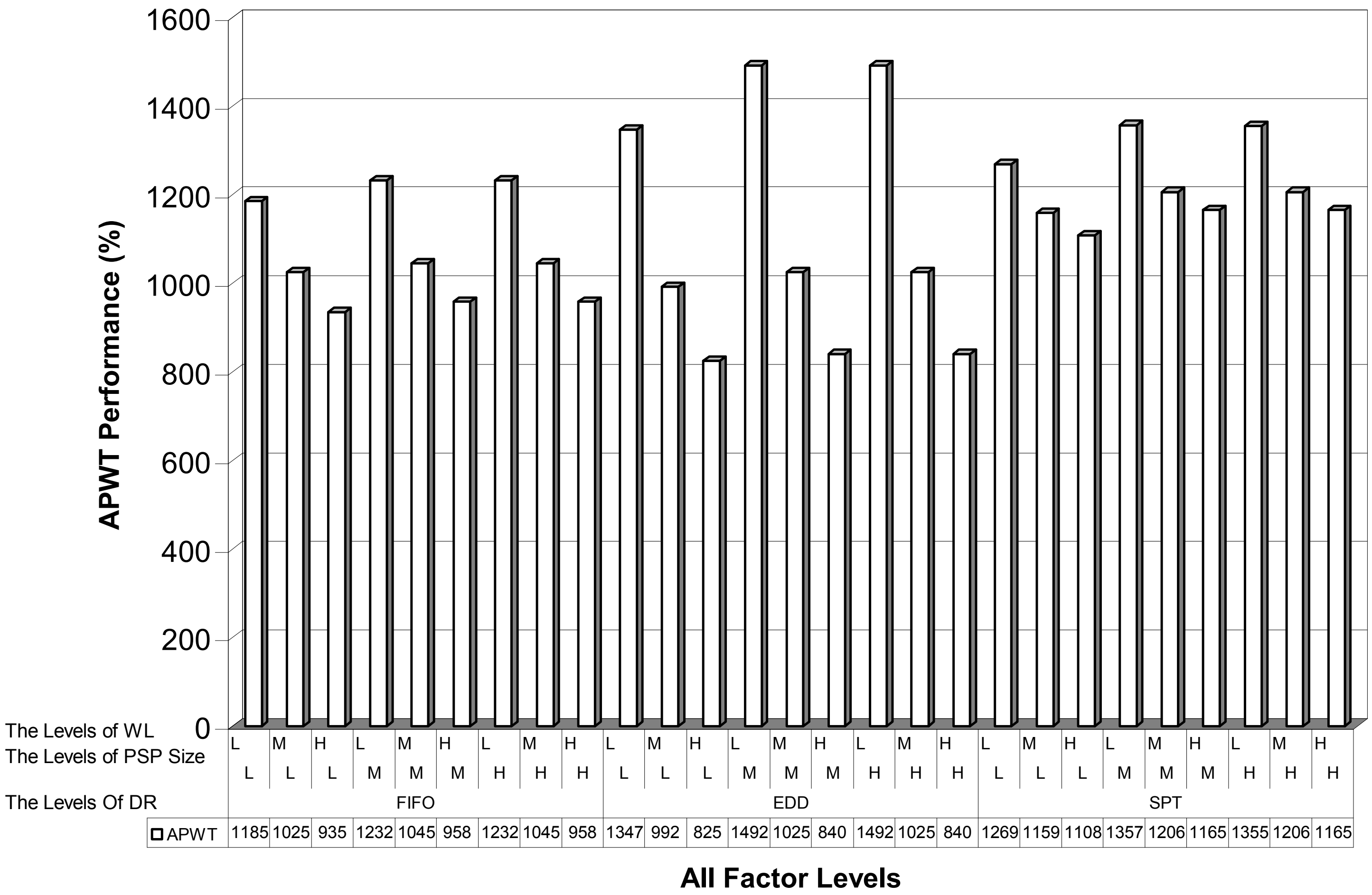


Figure A.49. APWT Performance with WCWT at high DF

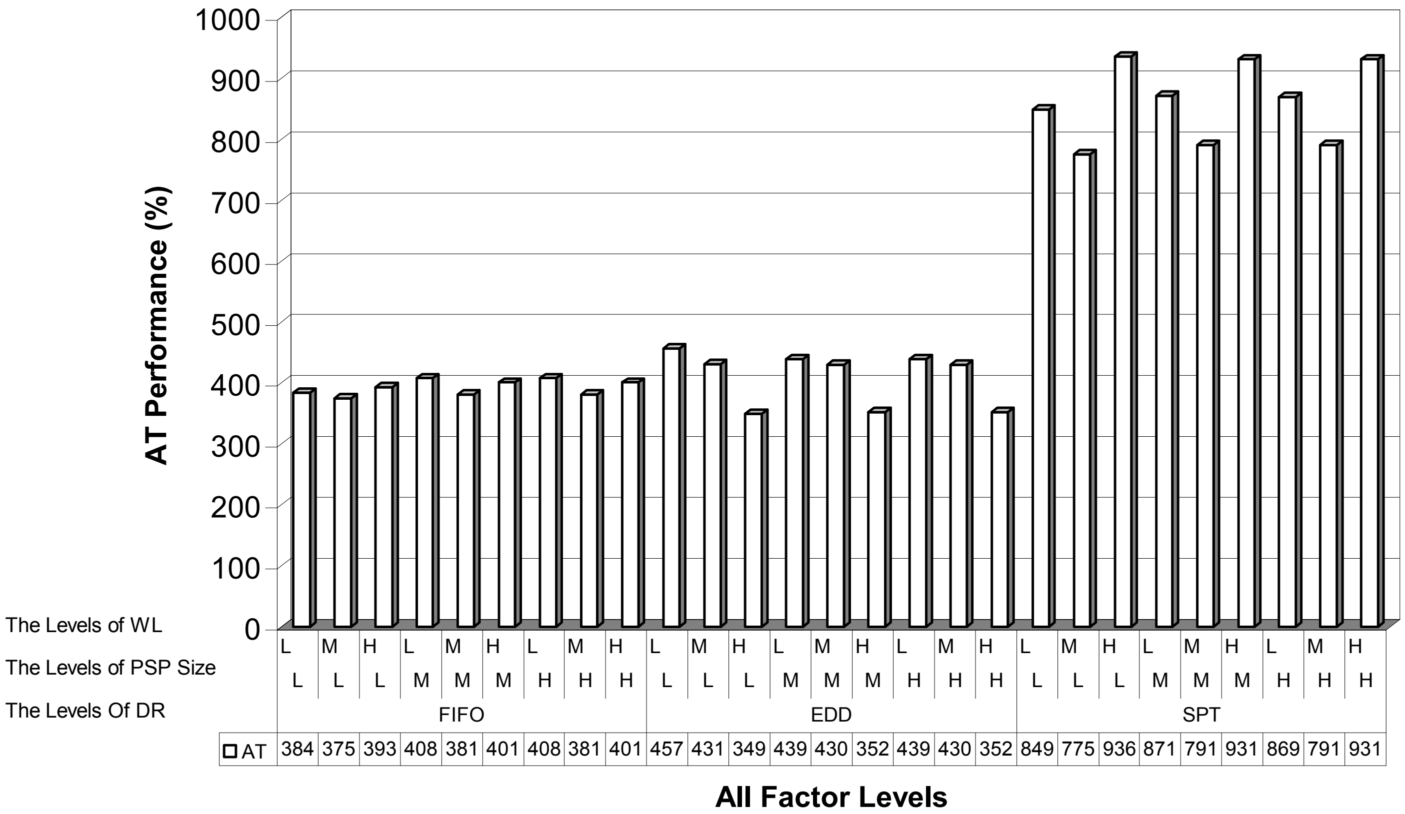


Figure A.50. AT Performance with WCWT at high DF

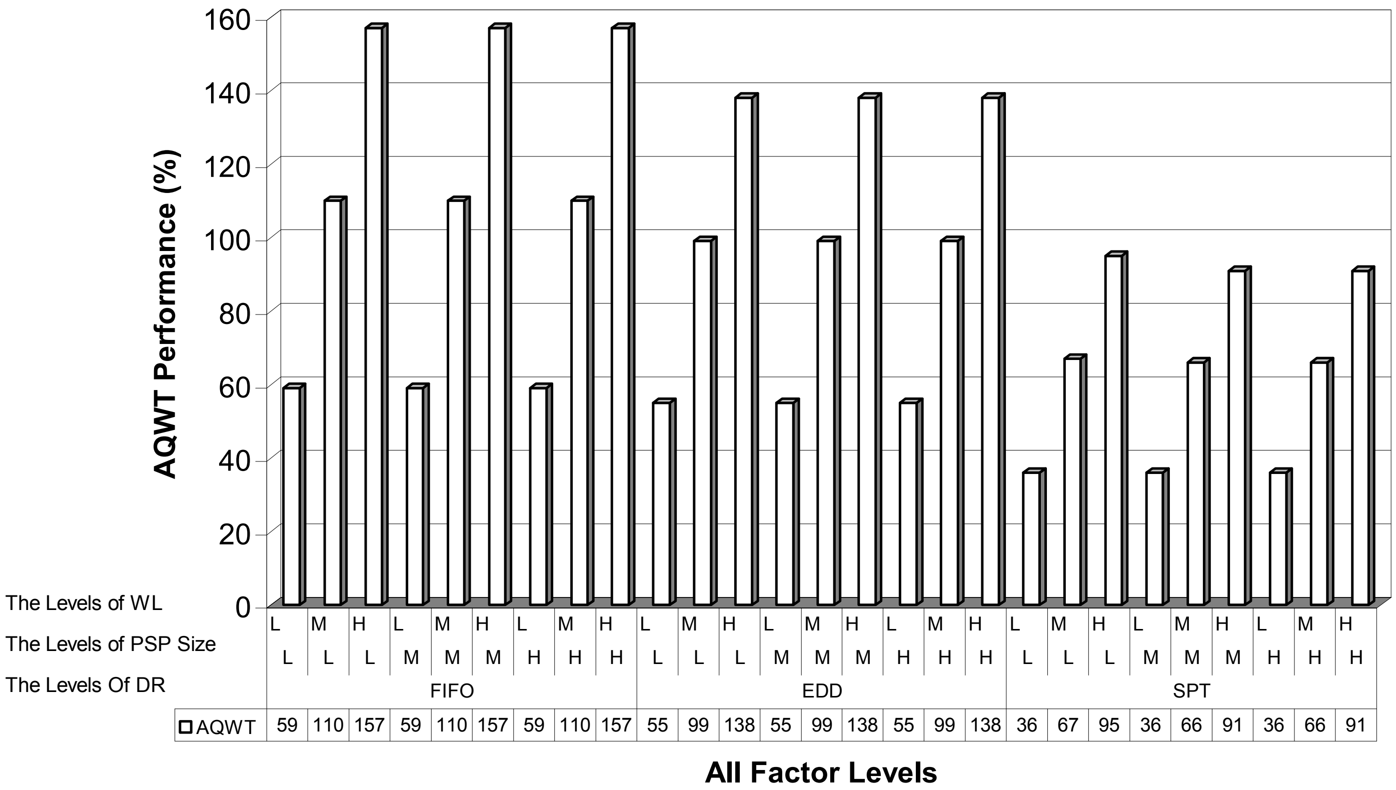


Figure A.51. AQWT Performance with WCWT at high DF

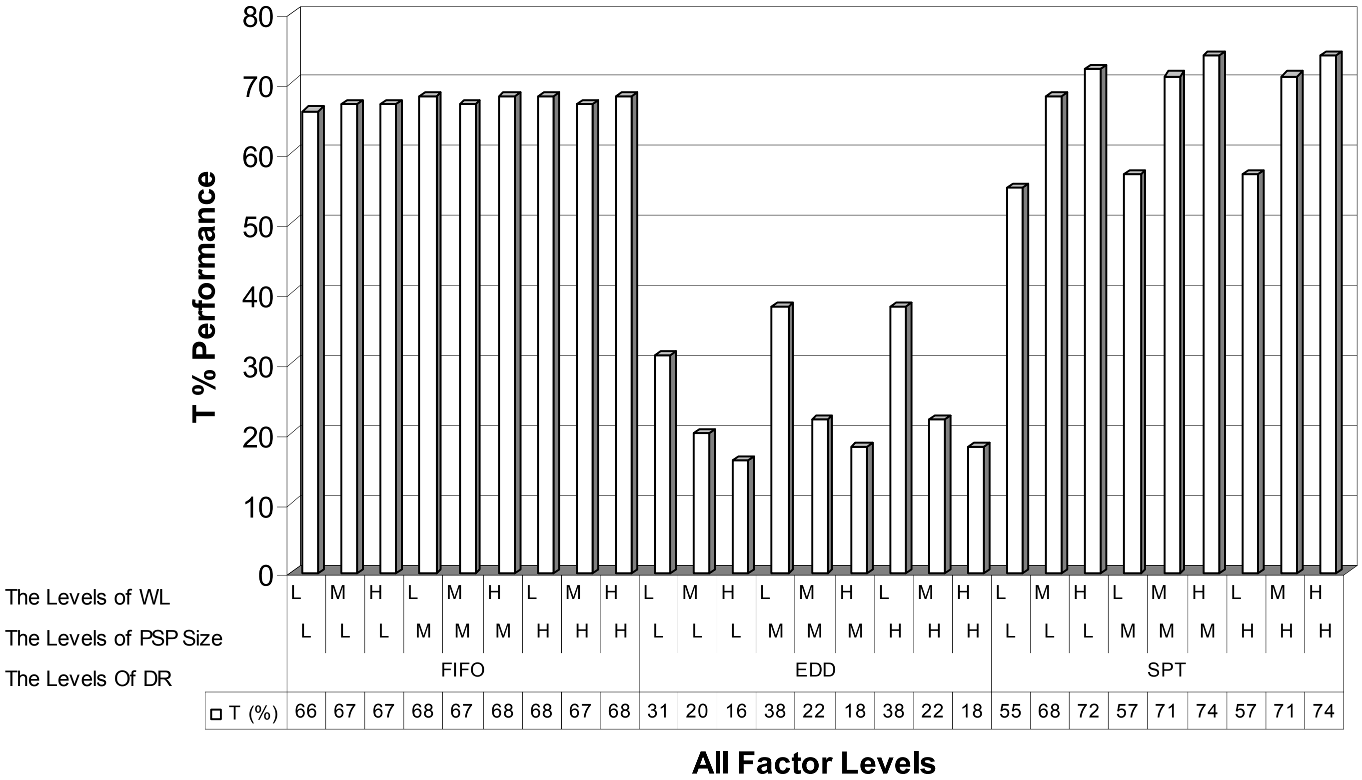


Figure A.52. T (%) Performance with WCWT at high DF

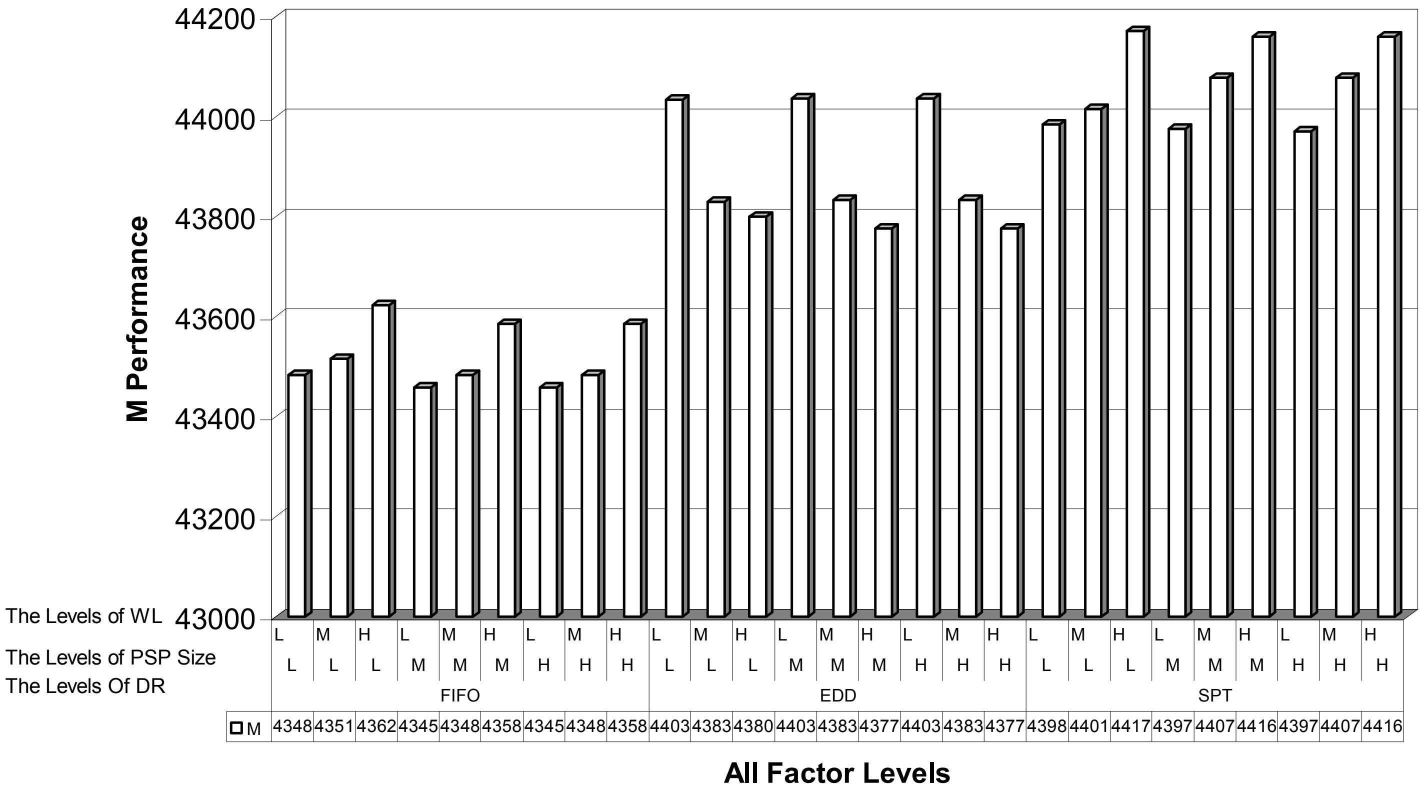


Figure A.53. M Performance with WCWT at high DF

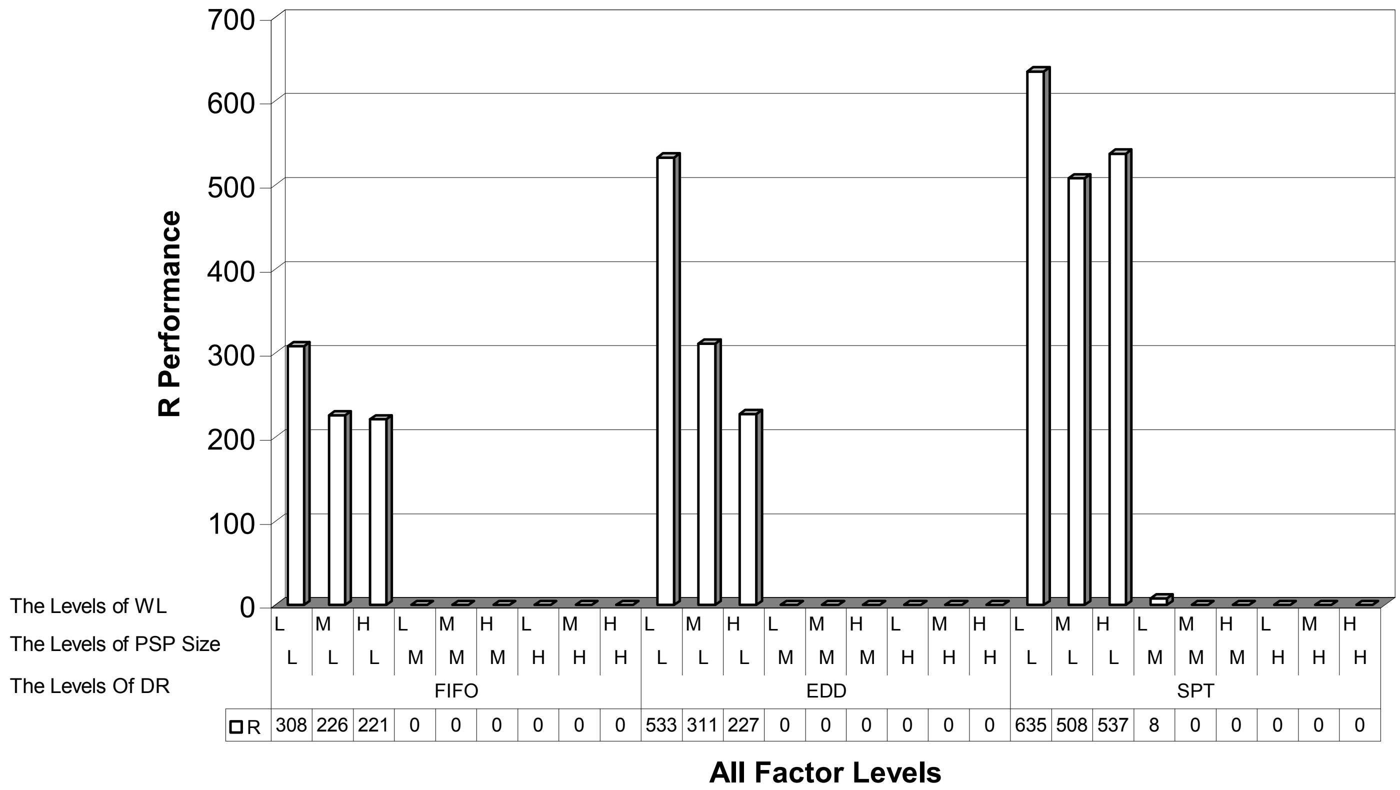


Figure A.54. R Performance with WCWT at high DF

Table A.12. Measures of main Performances with WCWT at high DF

DF	OR Mec.	DR	PSP Size	WL	MAPE (%)	MPE (%)	MLT	SFTT	APWT	AL	STD. L	AT	AE	AQWT	T (%)	E (%)	M	R
2	WCWT	FIFO	1000	50	22	05	1576	407	1185	200	497	384	-159	59	66	34	43483	308
			1000	100	19	07	1678	684	1025	199	468	375	-156	110	67	33	43516	226
			1000	150	18	07	1838	941	935	209	502	393	-165	157	67	33	43623	221
			2000	50	22	06	1616	408	1232	229	523	408	-151	59	68	32	43459	0
			2000	100	19	07	1695	684	1045	207	477	381	-154	110	67	33	43483	0
			2000	150	18	07	1857	941	958	220	514	401	-159	157	68	32	43586	0
			3000	50	22	06	1616	408	1232	229	523	408	-151	59	68	32	43459	0
			3000	100	19	07	1695	684	1045	207	477	381	-154	110	67	33	43483	0
			3000	150	18	07	1857	941	958	220	514	401	-159	157	68	32	43586	0
		EDD	1000	50	61	-47	1709	380	1347	-46	529	457	-268	55	31	69	44035	533
			1000	100	96	-86	1583	615	992	-189	479	431	-343	99	20	80	43830	311
			1000	150	104	-97	1621	823	825	-236	418	349	-347	138	16	84	43800	227
			2000	50	55	-41	1854	383	1492	9	511	439	-237	55	38	62	44037	0
			2000	100	93	-82	1614	617	1025	-161	482	430	-325	99	22	78	43834	0
			2000	150	102	-94	1633	821	840	-220	420	352	-339	138	18	82	43777	0
			3000	50	55	-41	1854	383	1492	9	511	439	-237	55	38	62	44037	0
			3000	100	93	-82	1614	617	1025	-161	482	430	-325	99	22	78	43834	0
			3000	150	102	-94	1633	821	840	-220	420	352	-339	138	18	82	43777	0
		SPT	1000	50	192	-152	1537	281	1269	96	3083	849	-822	36	55	45	43984	635
			1000	100	172	-119	1585	446	1159	159	3244	775	-1168	67	68	32	44016	508
			1000	150	189	-125	1686	602	1108	277	3631	936	-1418	95	72	28	44171	537
			2000	50	173	-132	1620	277	1357	153	3034	871	-810	36	57	43	43976	8
			2000	100	163	-109	1626	442	1206	224	3164	791	-1142	66	71	29	44078	0
			2000	150	172	-108	1721	583	1165	314	3635	931	-1432	91	74	26	44160	0
			3000	50	173	-132	1617	277	1355	153	3023	869	-807	36	57	43	43971	0
			3000	100	163	-109	1626	442	1206	224	3164	791	-1142	66	71	29	44078	0
			3000	150	172	-108	1721	583	1165	314	3635	931	-1432	91	74	26	44160	0

APPENDIX B

PERFORMANCE OF THE SHOP FOR EACH PSP SIZE WITH RESPECT TO ALL OTHER FACTOR COMBINATIONS

This appendix provides graphical illustrations of MAPE, MLT, SFTT, AT, AQWT, T (%), M, and R performances with OR mechanisms at all other factor level combinations with respect to each PSP size, separately.

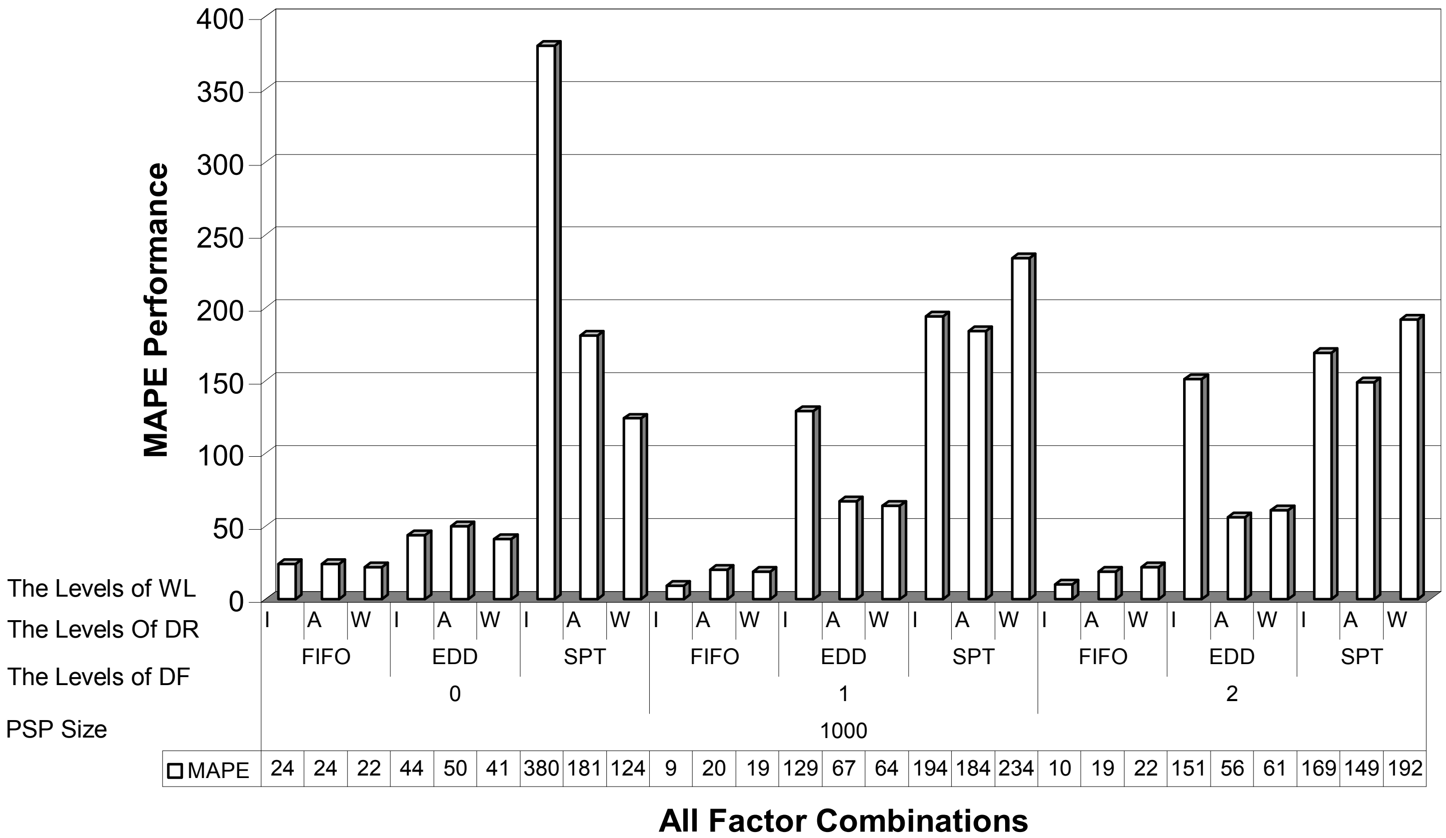


Figure B.1. MAPE with OR mechanisms (PSP Size: 1000)

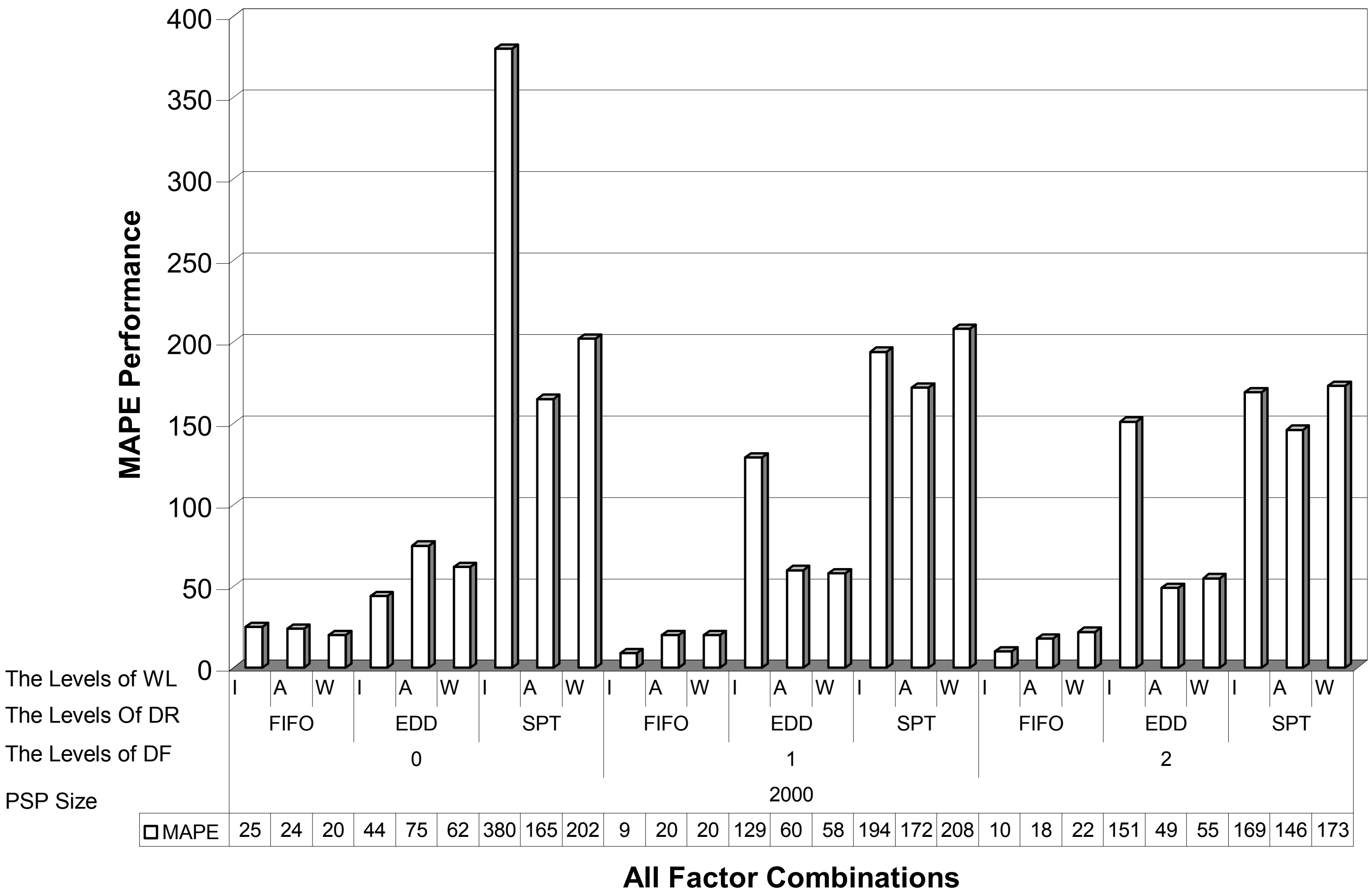


Figure B.2. MAPE with OR mechanisms (PSP Size: 2000)

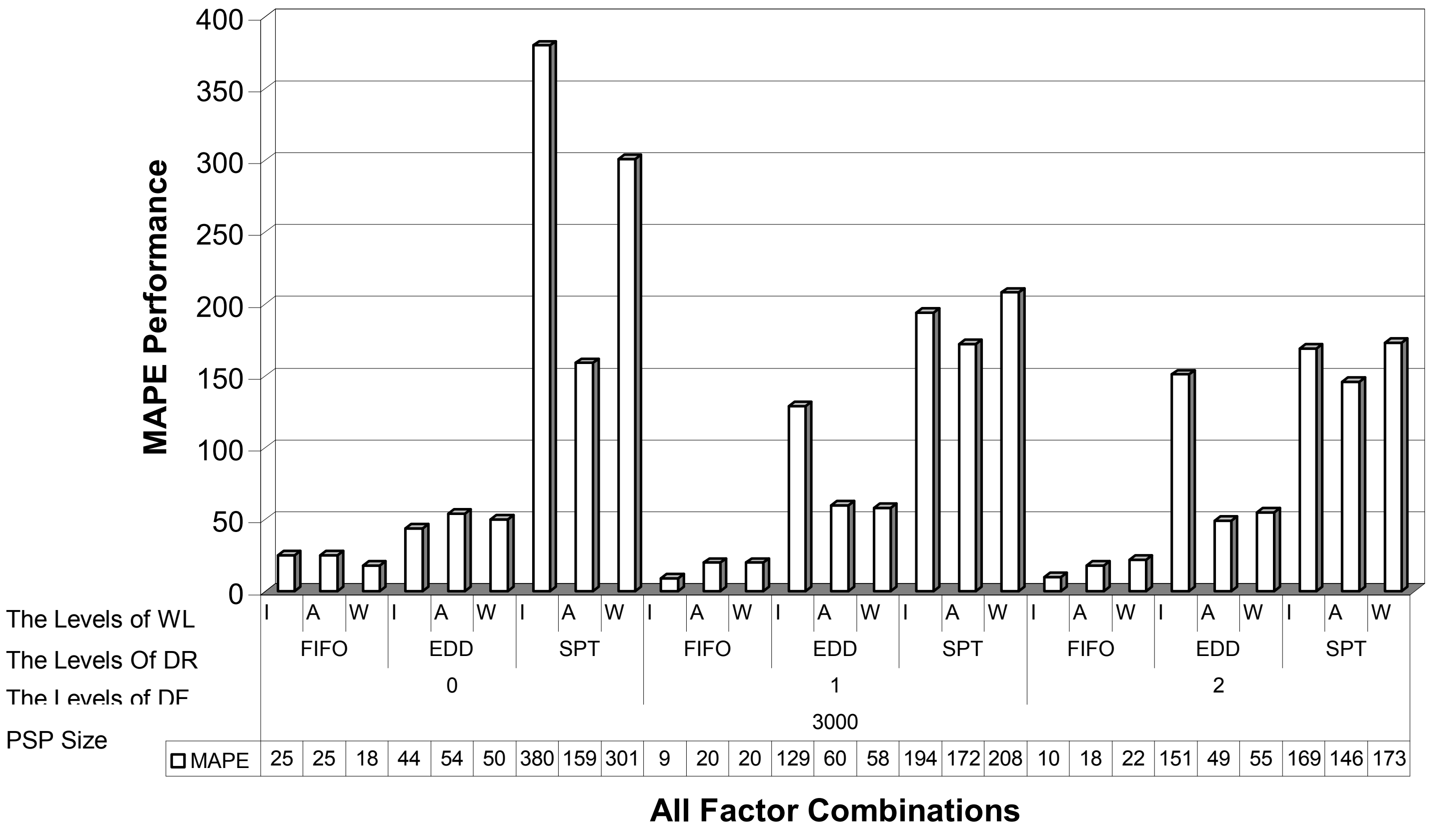


Figure B.3. MAPE with OR mechanisms (PSP Size: 3000)

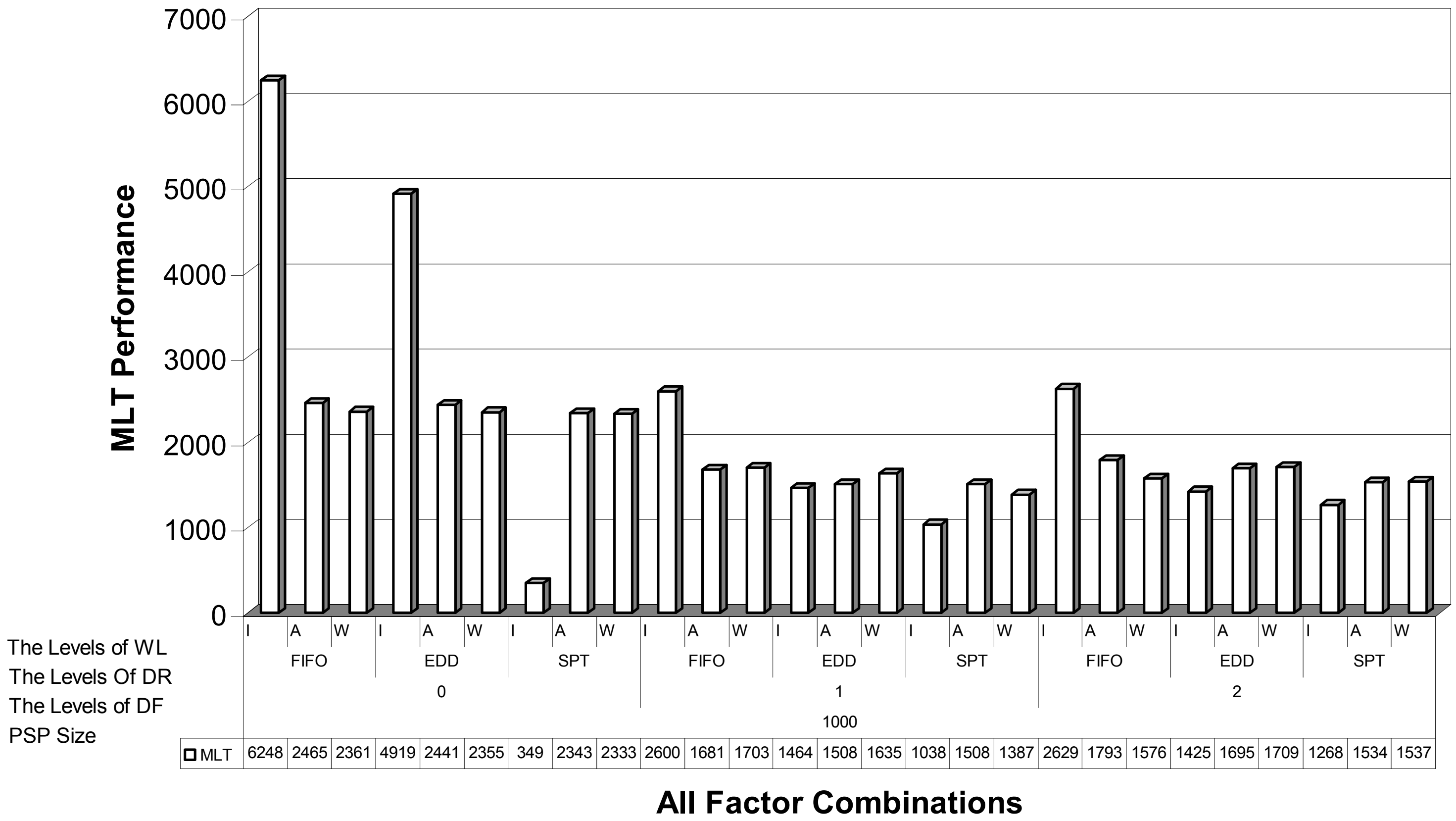


Figure B.4. MLT with OR mechanisms (PSP Size: 1000)

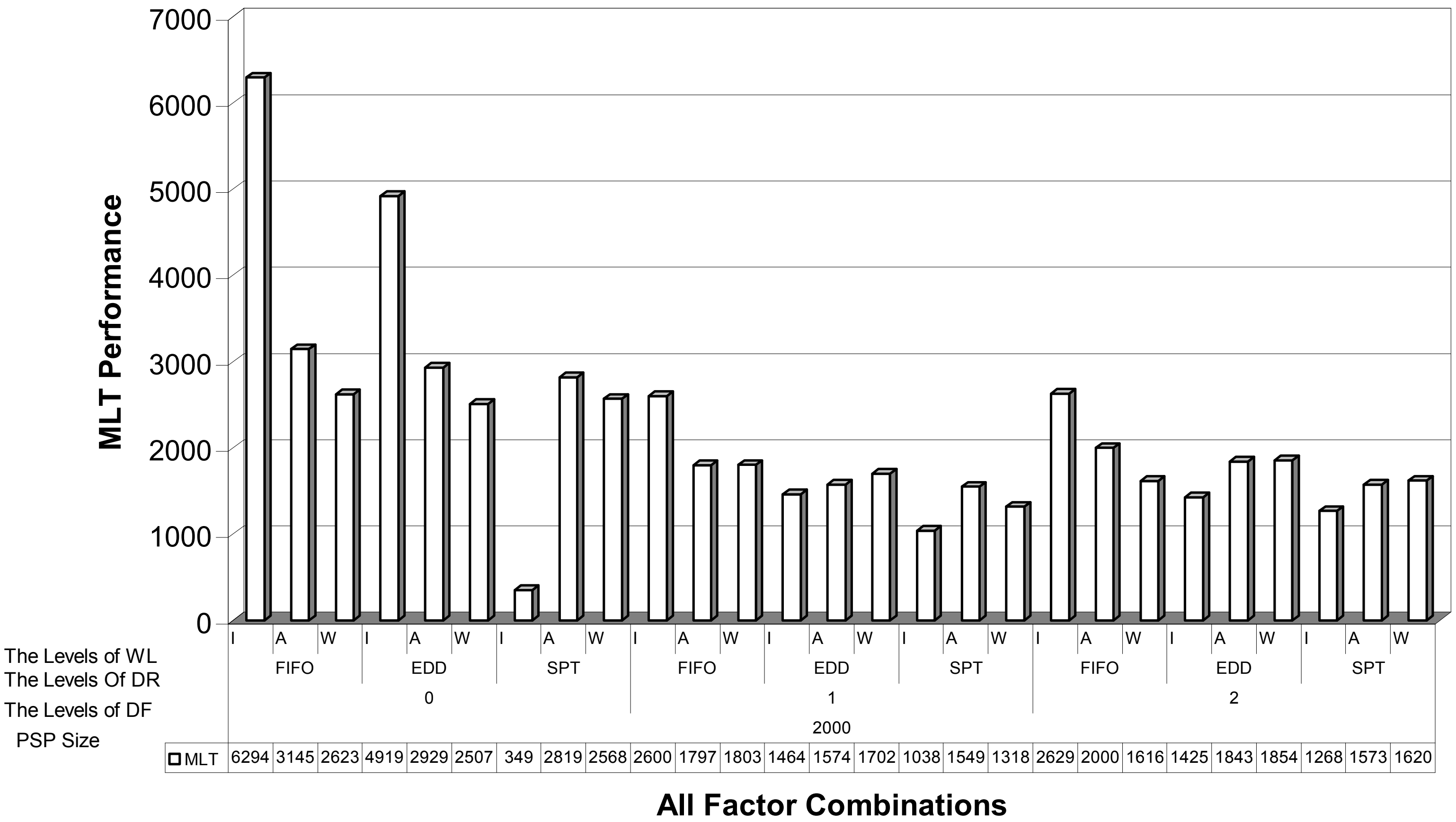


Figure B.5. MLT with OR mechanisms (PSP Size: 2000)

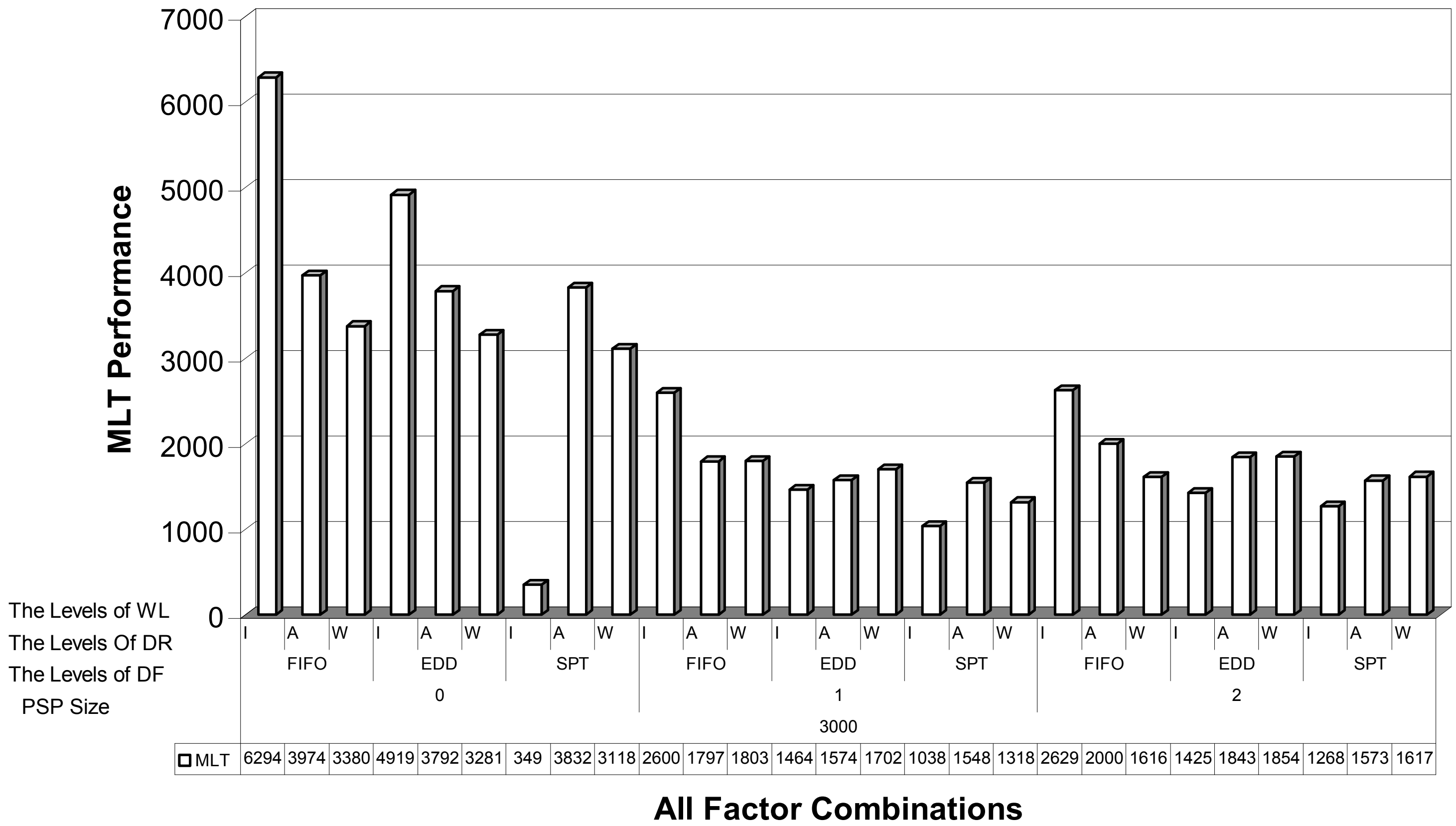


Figure B.6. MLT with OR mechanisms (PSP Size: 3000)

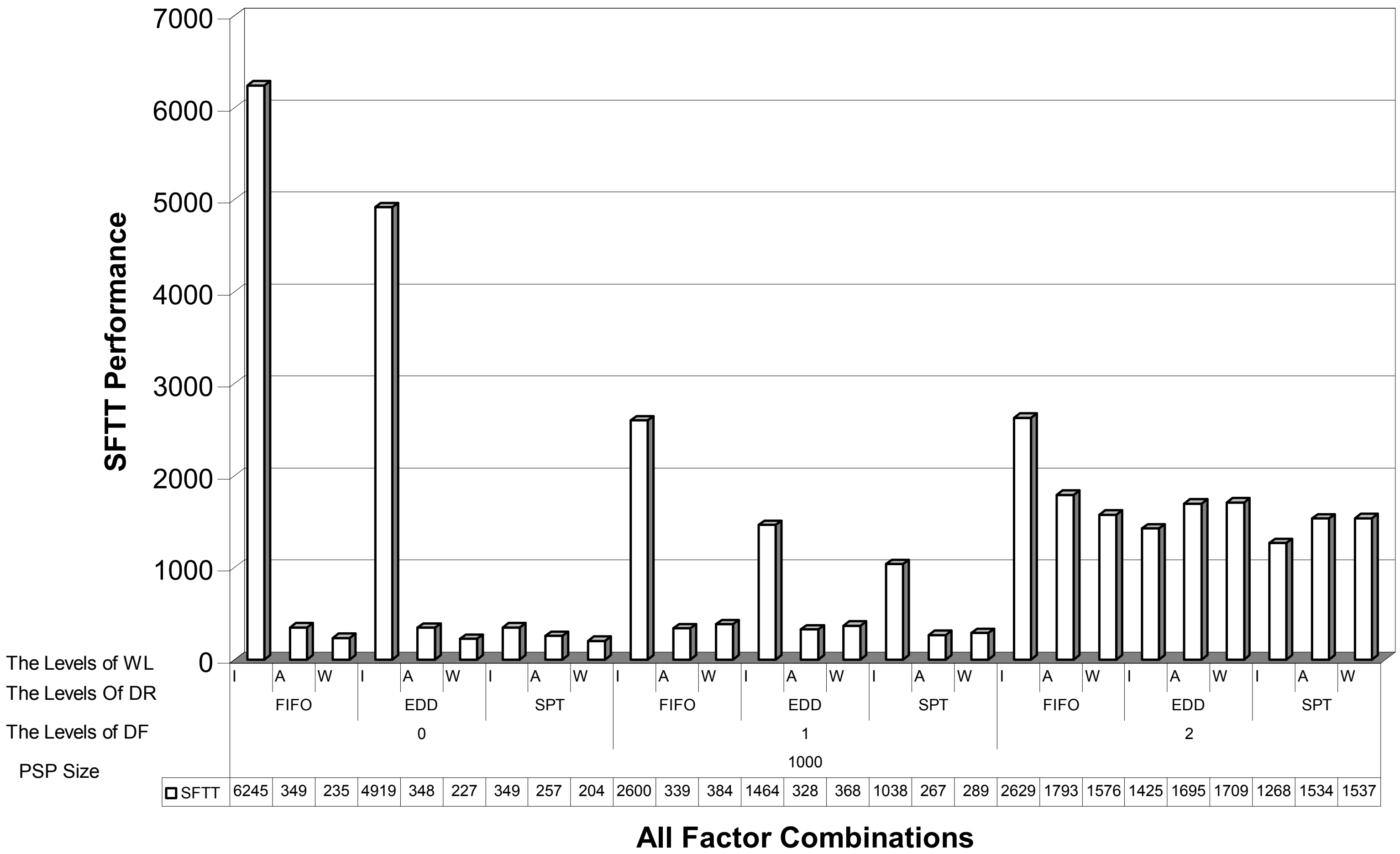


Figure B.7. SFTT with OR mechanisms (PSP Size: 1000)

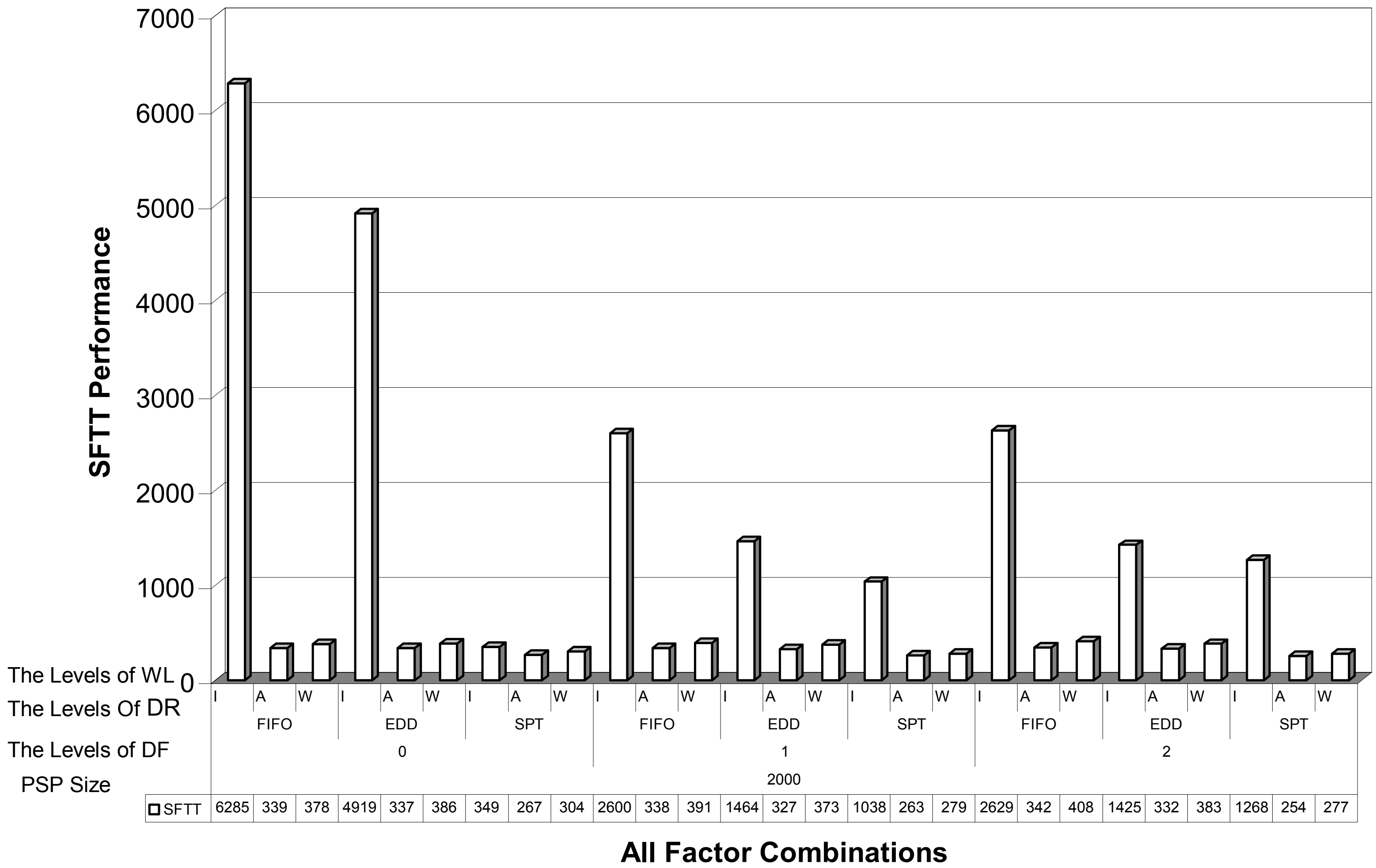


Figure B.8. SFTT with OR mechanisms (PSP Size: 2000)

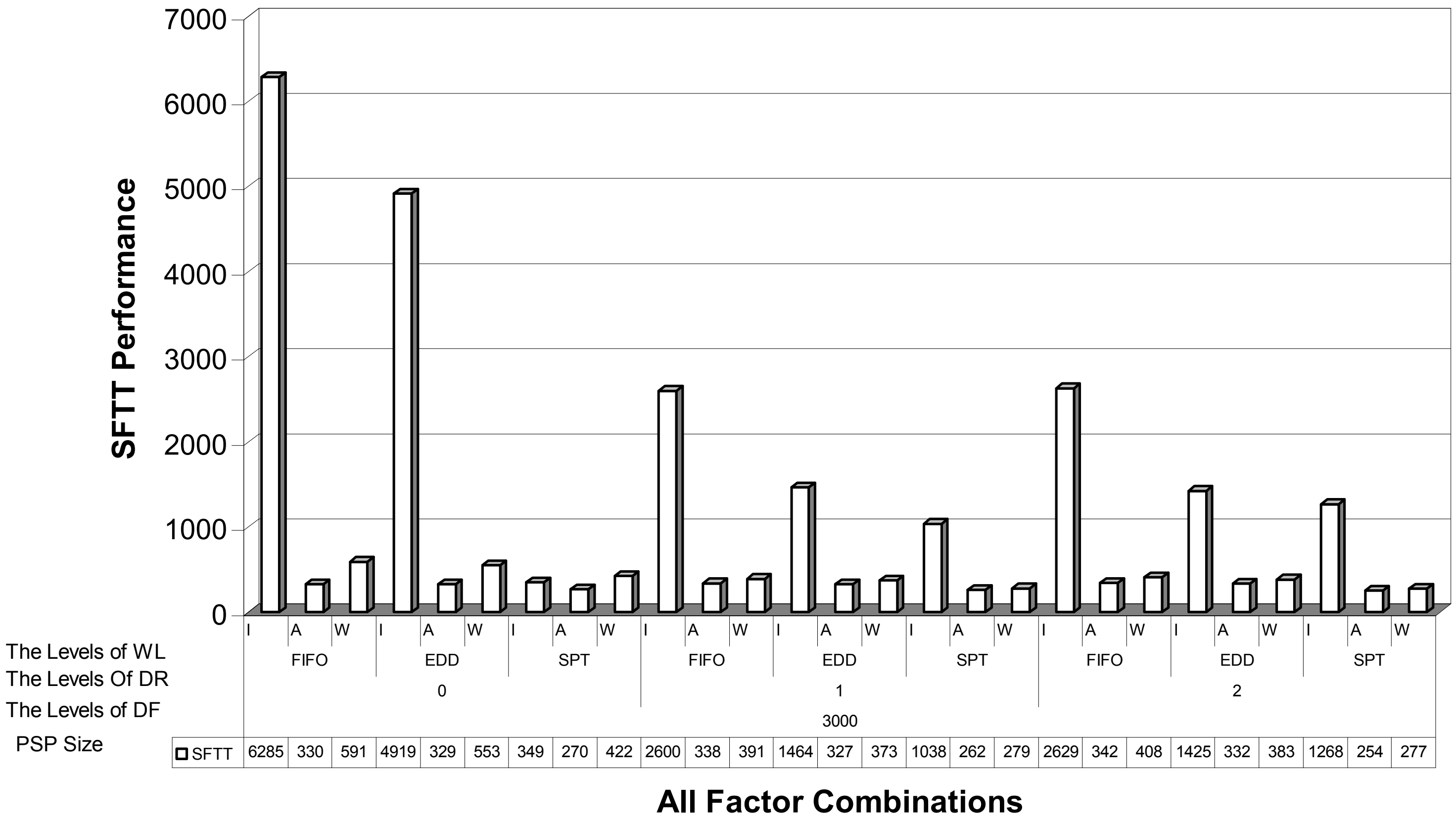


Figure B.9. SFTT with OR mechanisms (PSP Size: 3000)

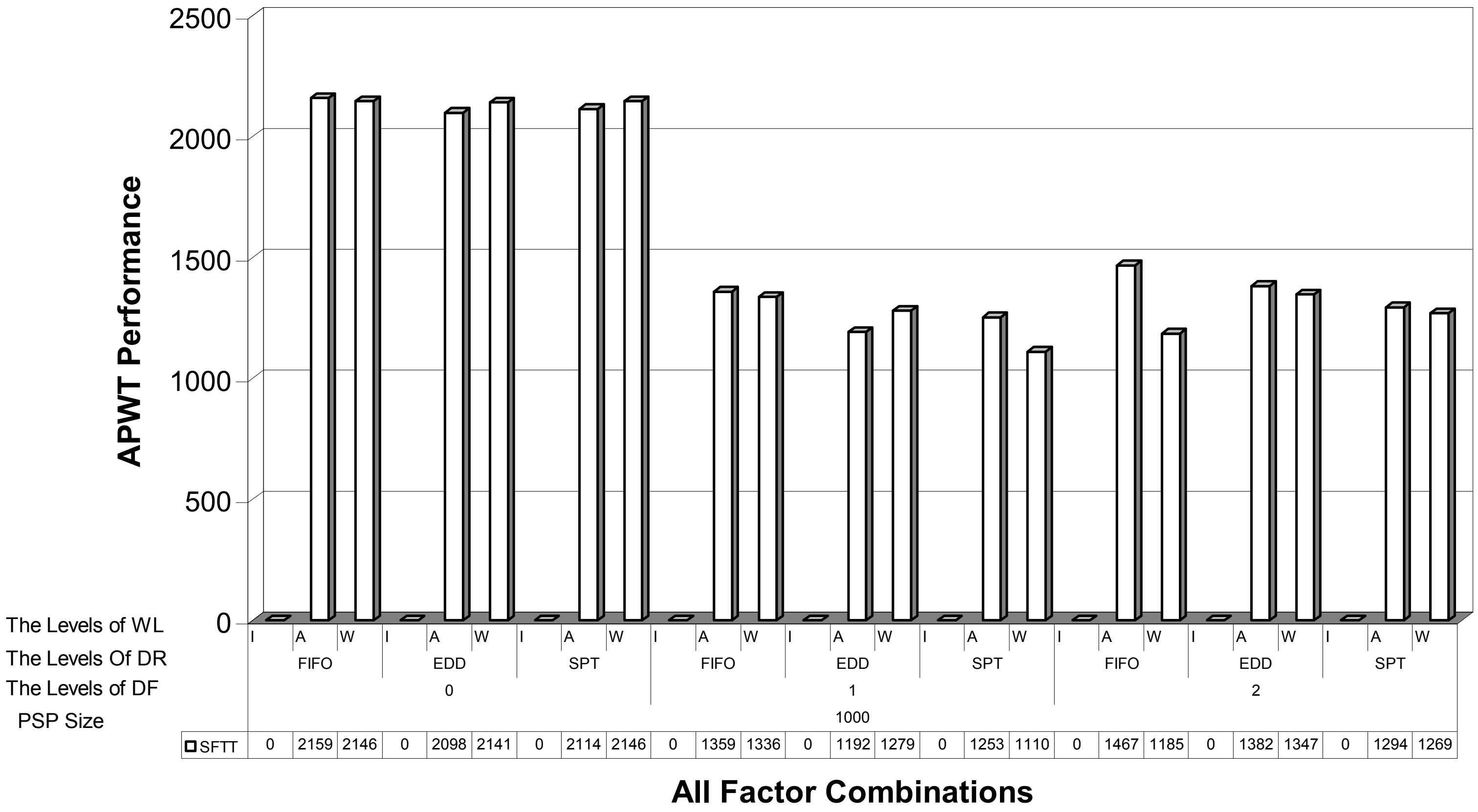


Figure B.10. APWT with OR mechanisms (PSP Size: 1000)

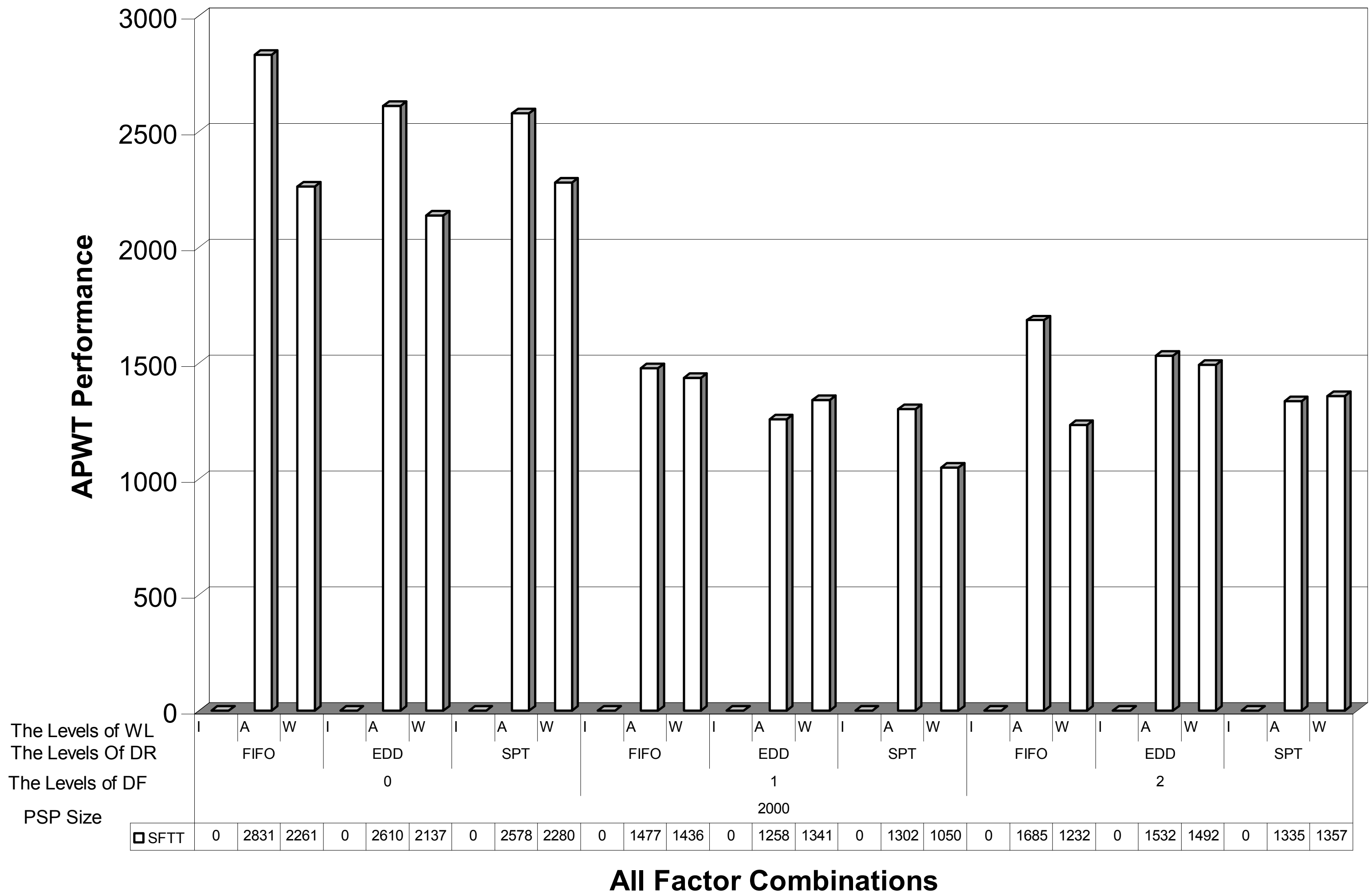


Figure B.11. APWT with OR mechanisms (PSP Size: 2000)

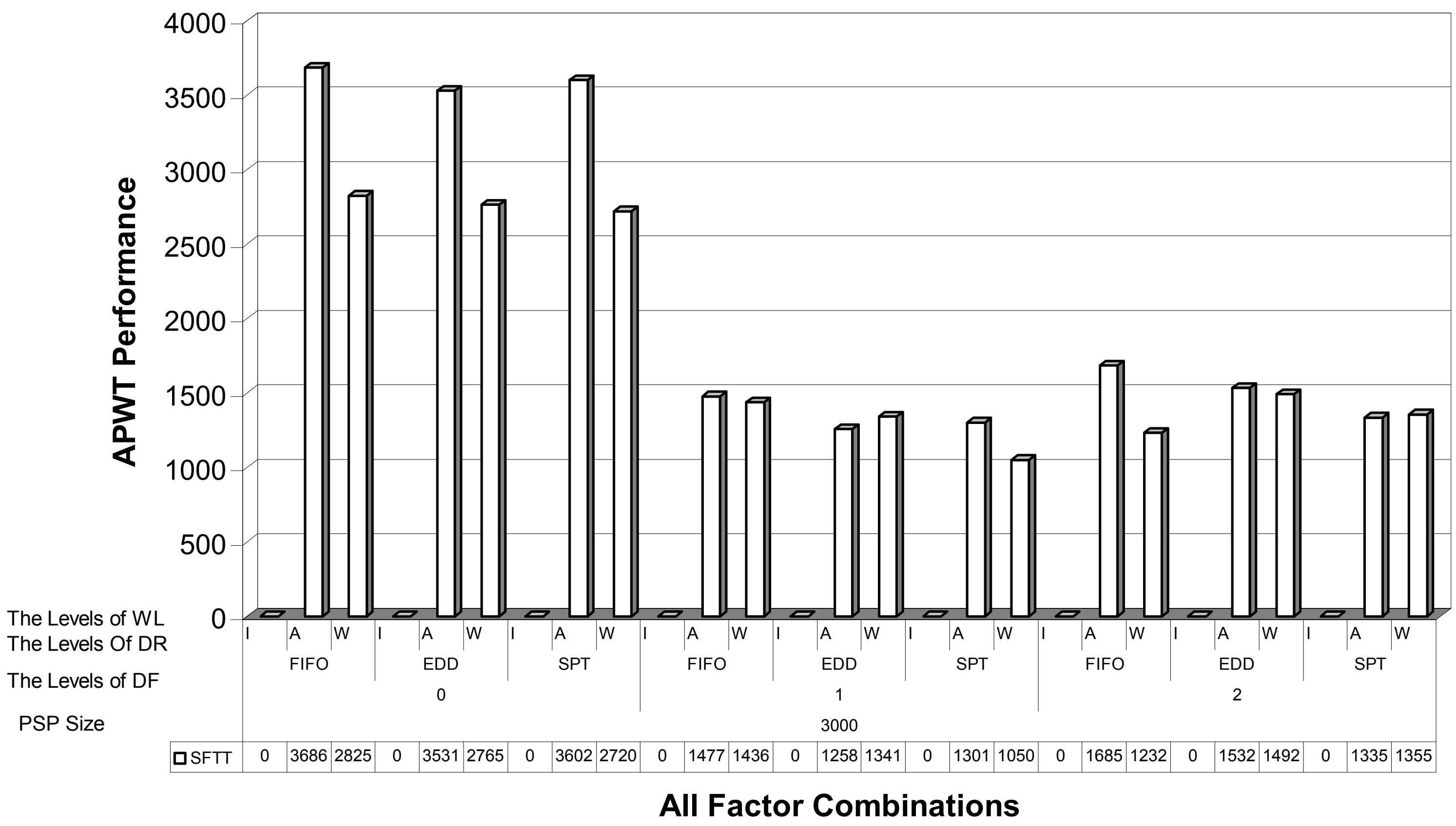


Figure B.12. APWT with OR mechanisms (PSP Size: 3000)

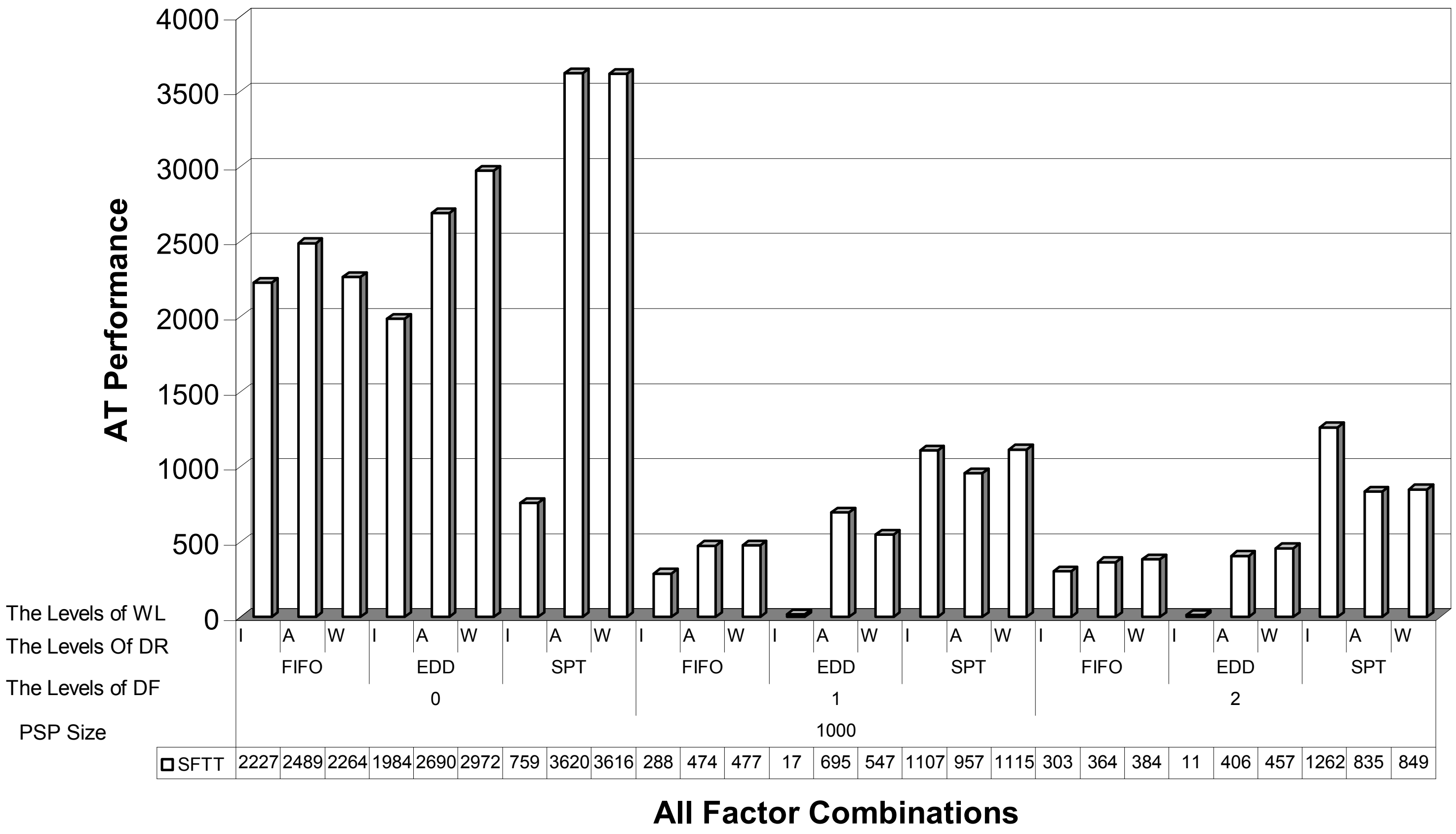


Figure B.13. AT with OR mechanisms (PSP Size: 1000)

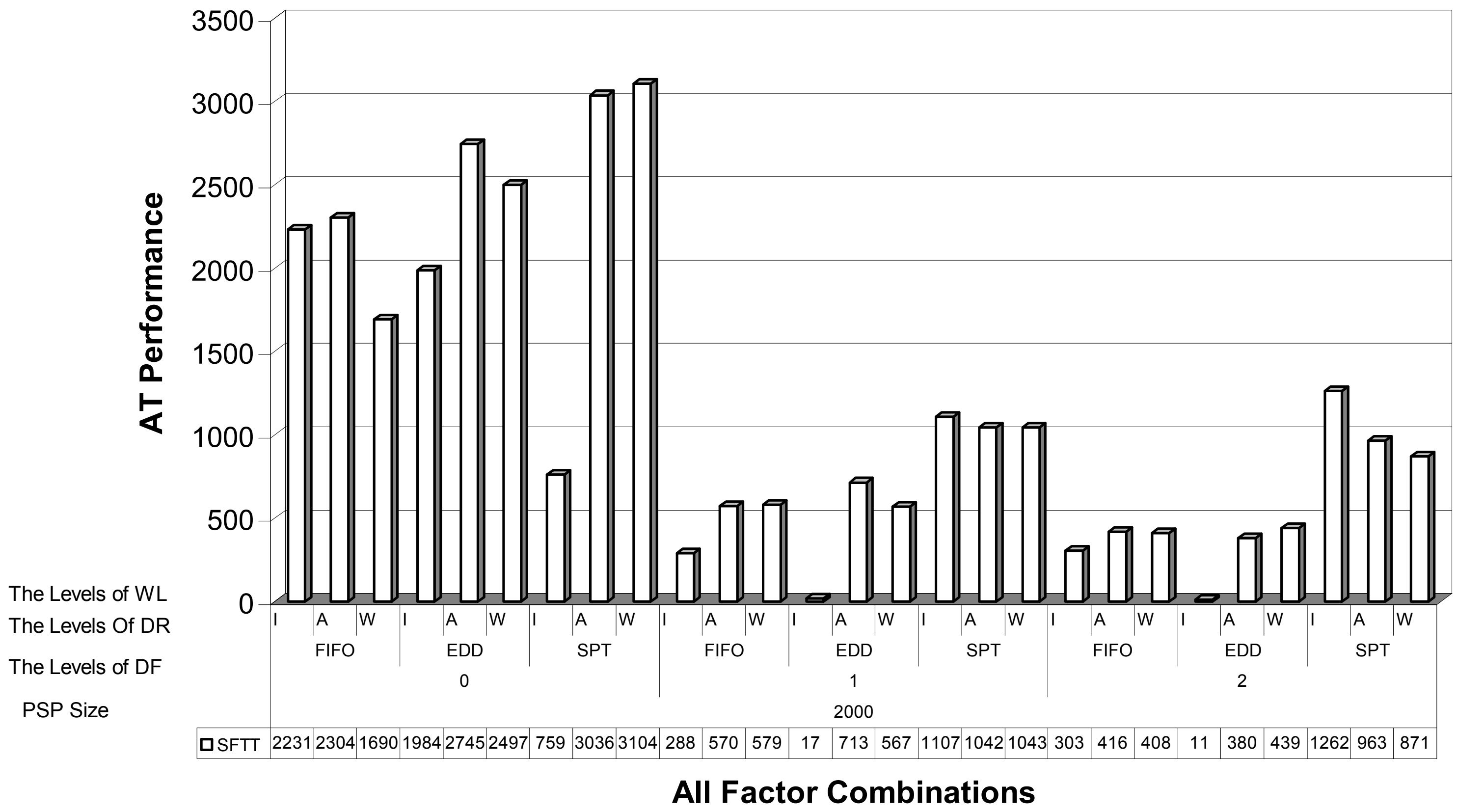


Figure B.14. AT with OR mechanisms (PSP Size: 2000)

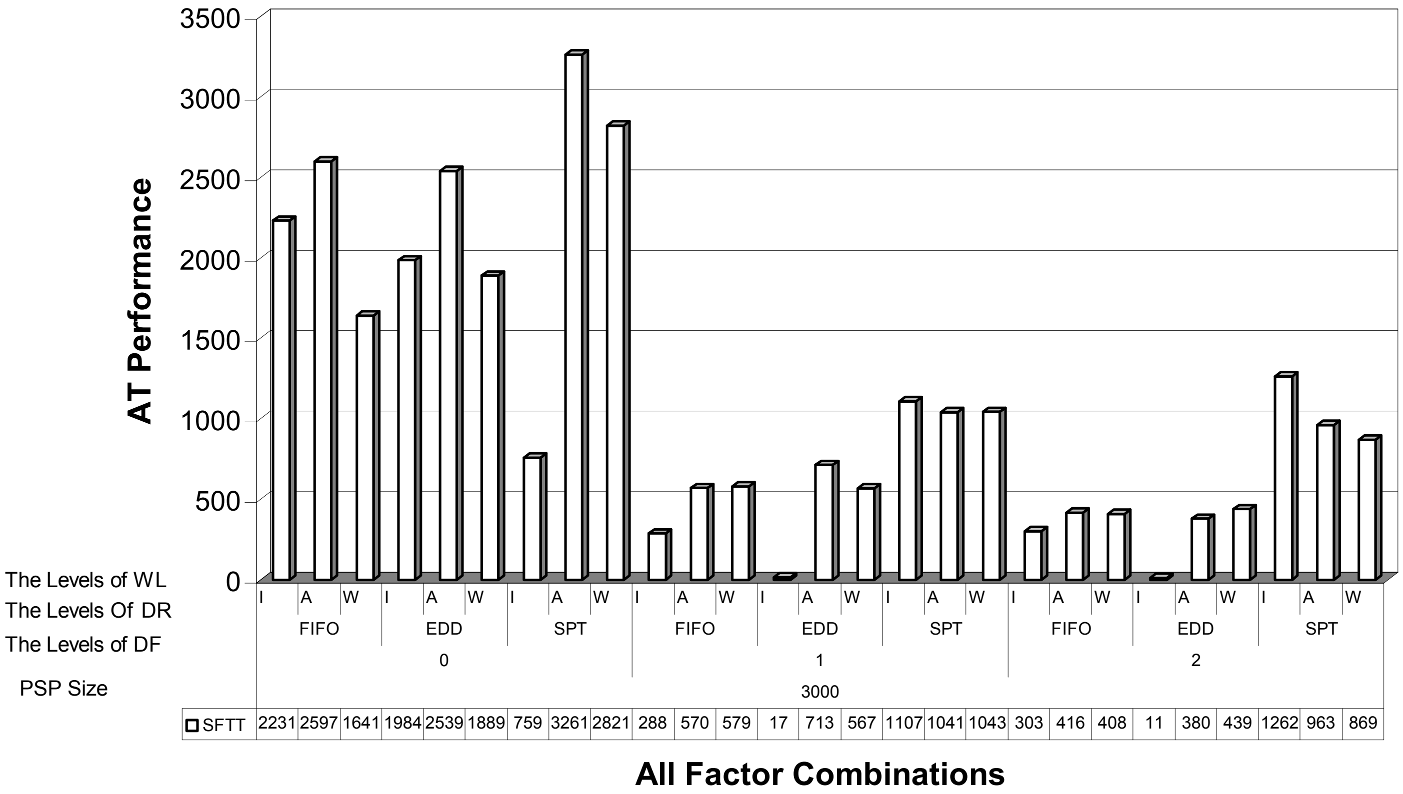


Figure B.15. AT with OR mechanisms (PSP Size: 3000)

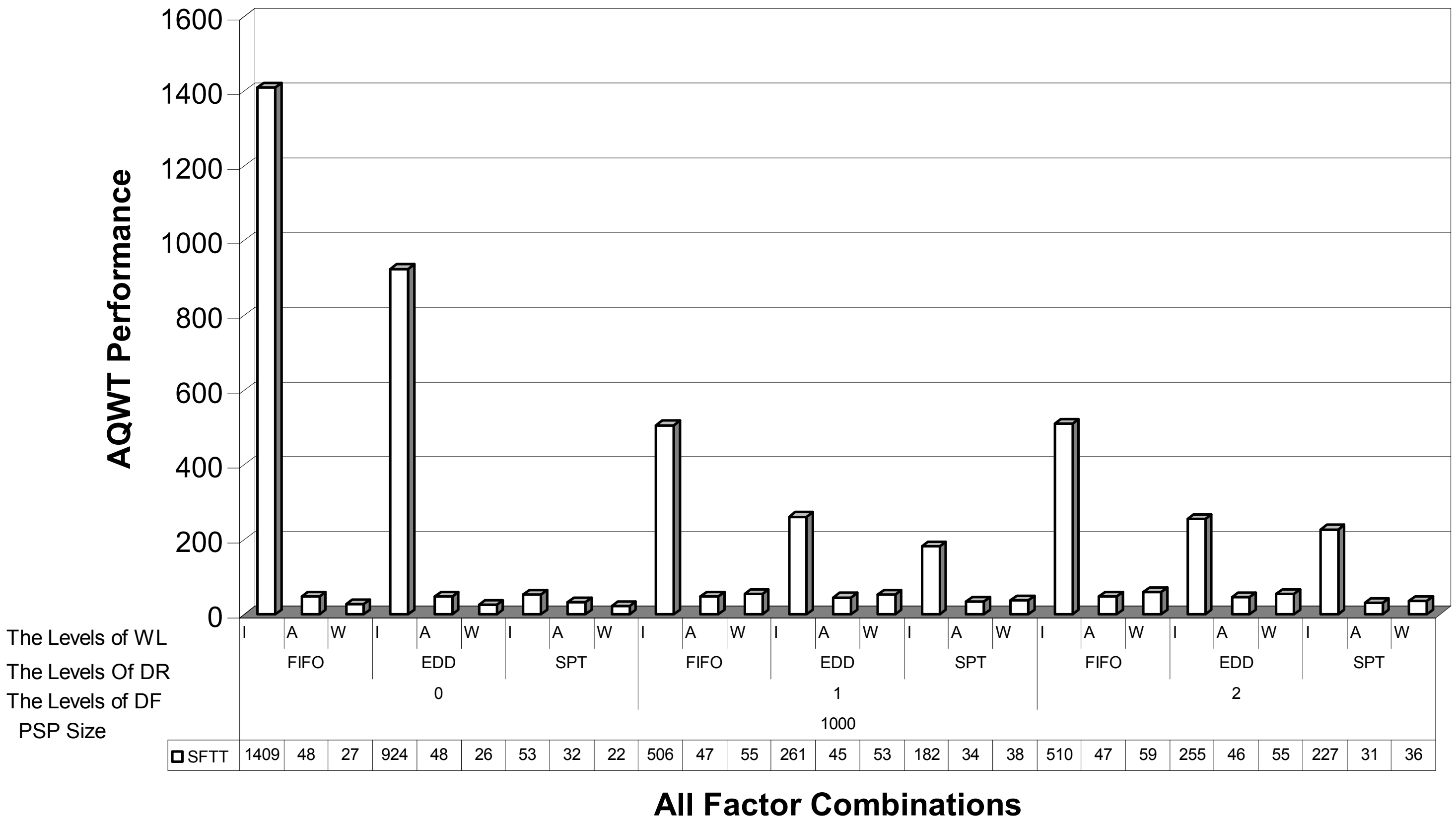


Figure B.16. AQWT with OR mechanisms (PSP Size: 1000)

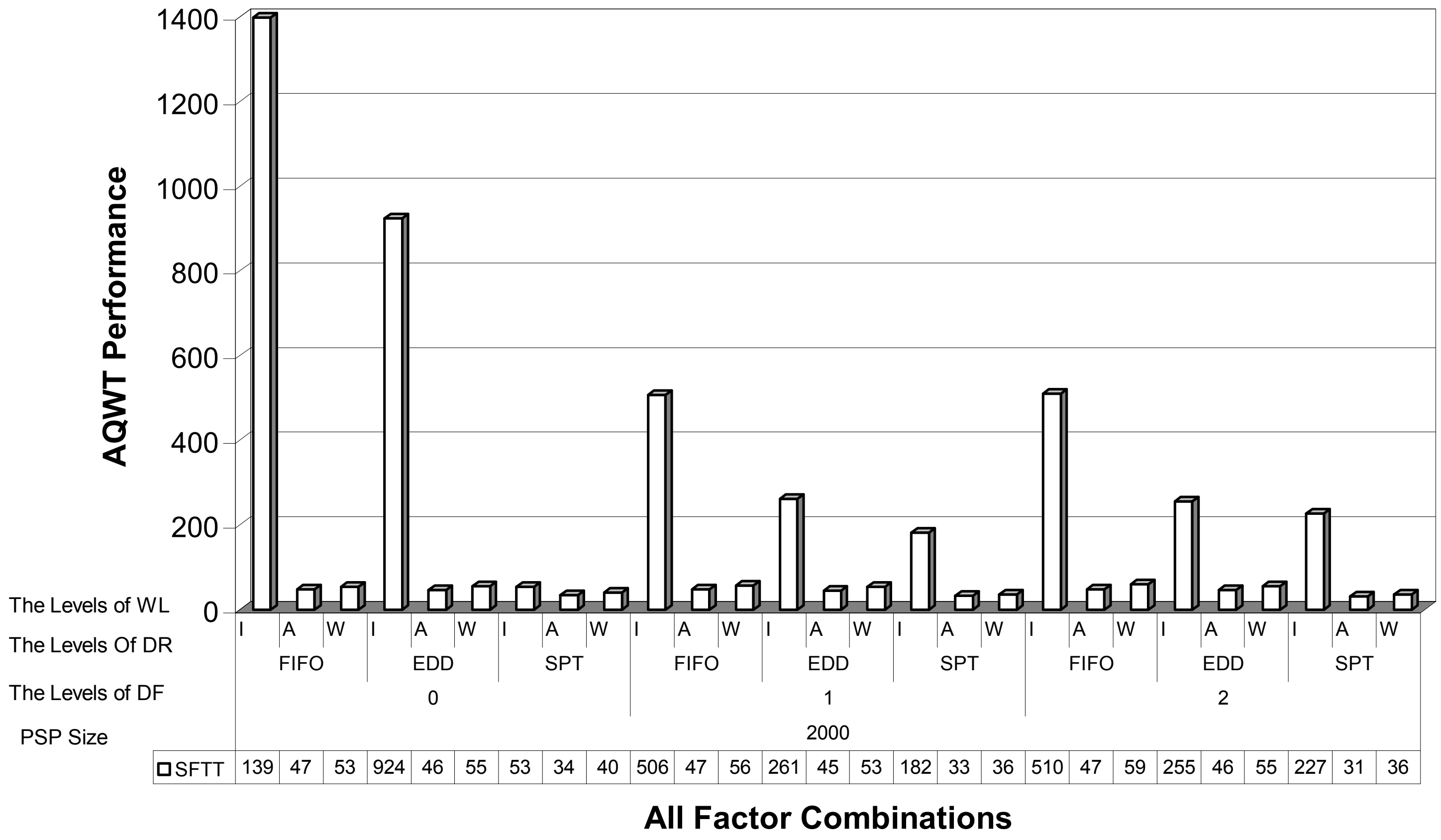


Figure B.17. AQWT with OR mechanisms (PSP Size: 2000)

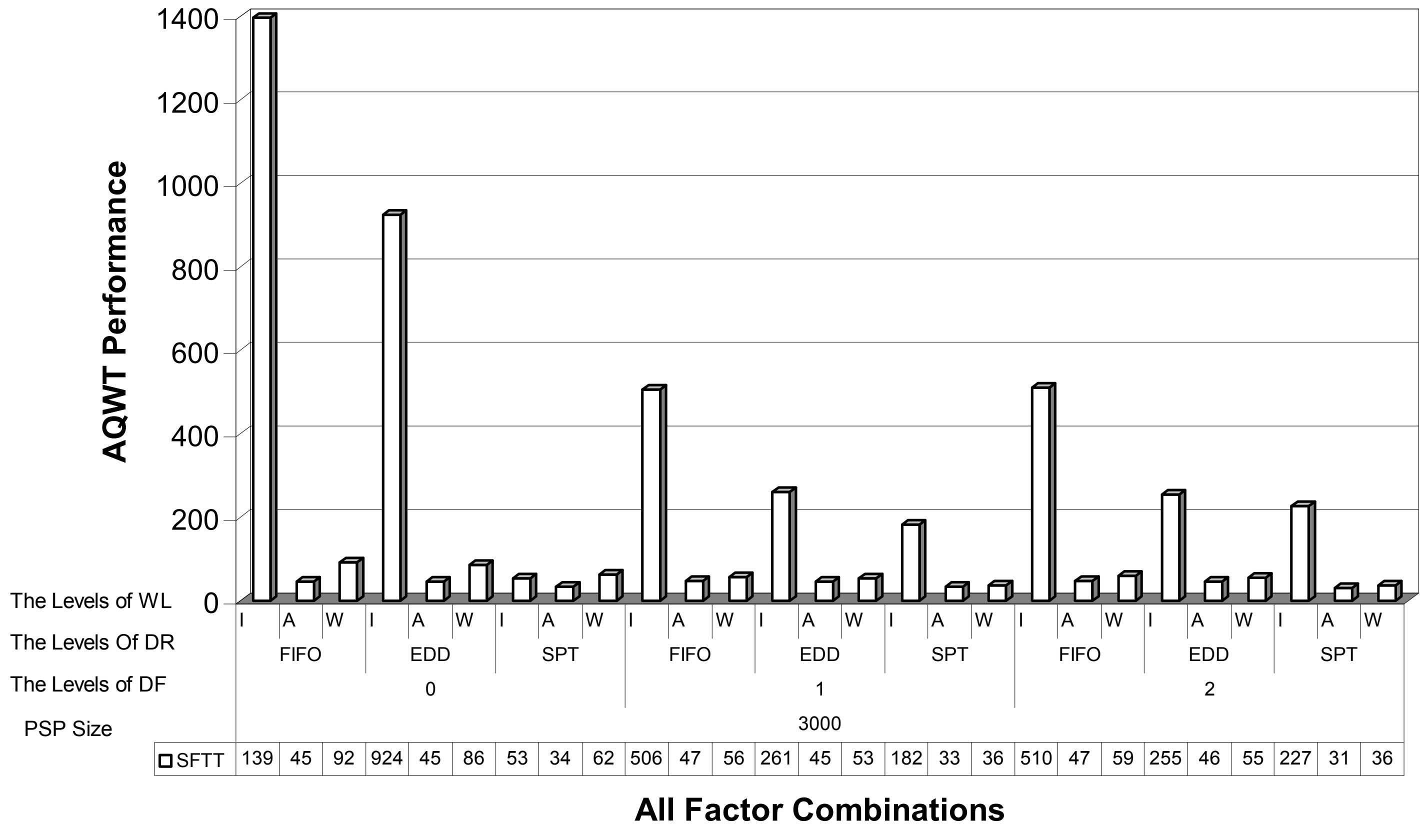


Figure B.18. AQWT with OR mechanisms (PSP Size: 3000)

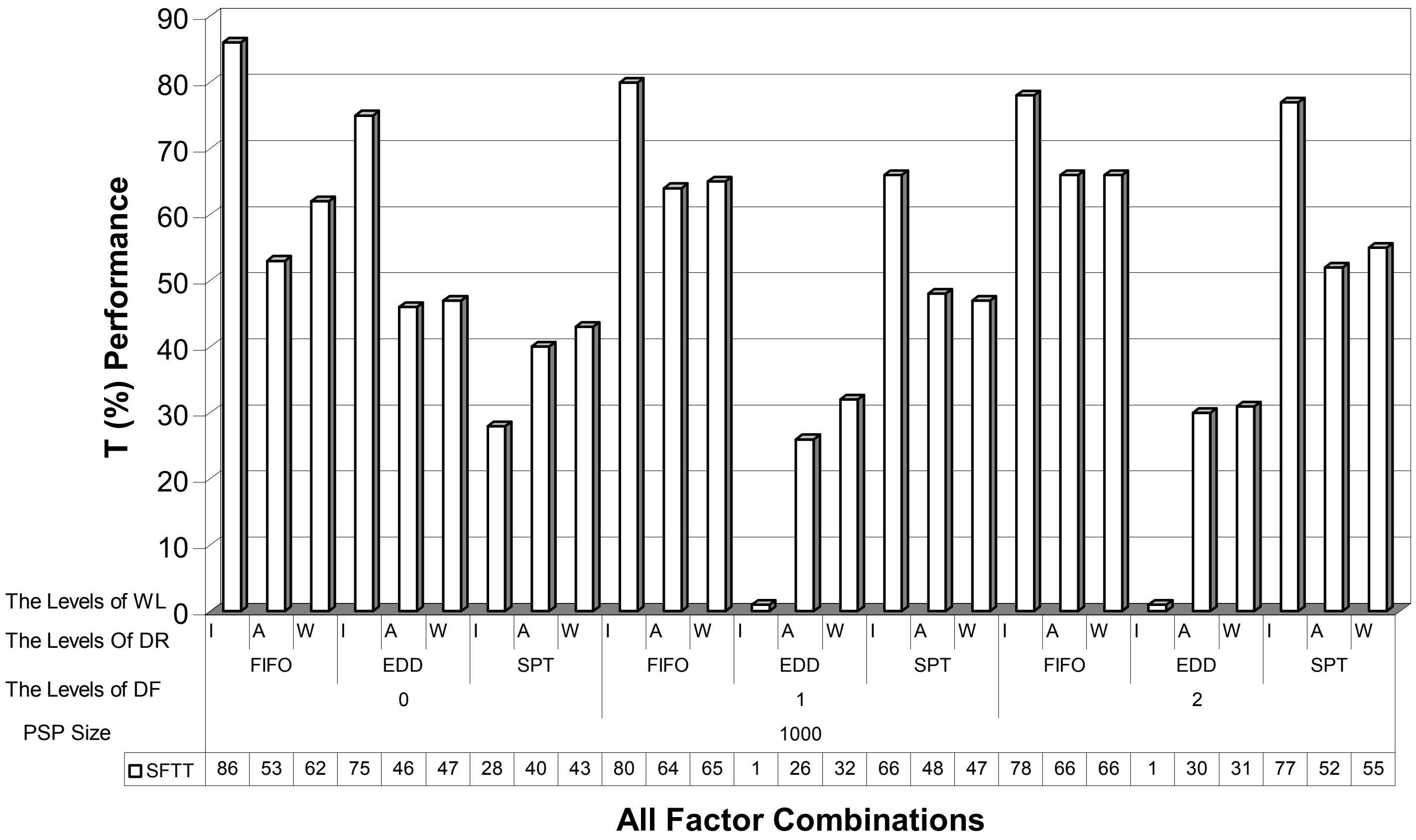


Figure B.19. T (%) with OR mechanisms (PSP Size: 1000)

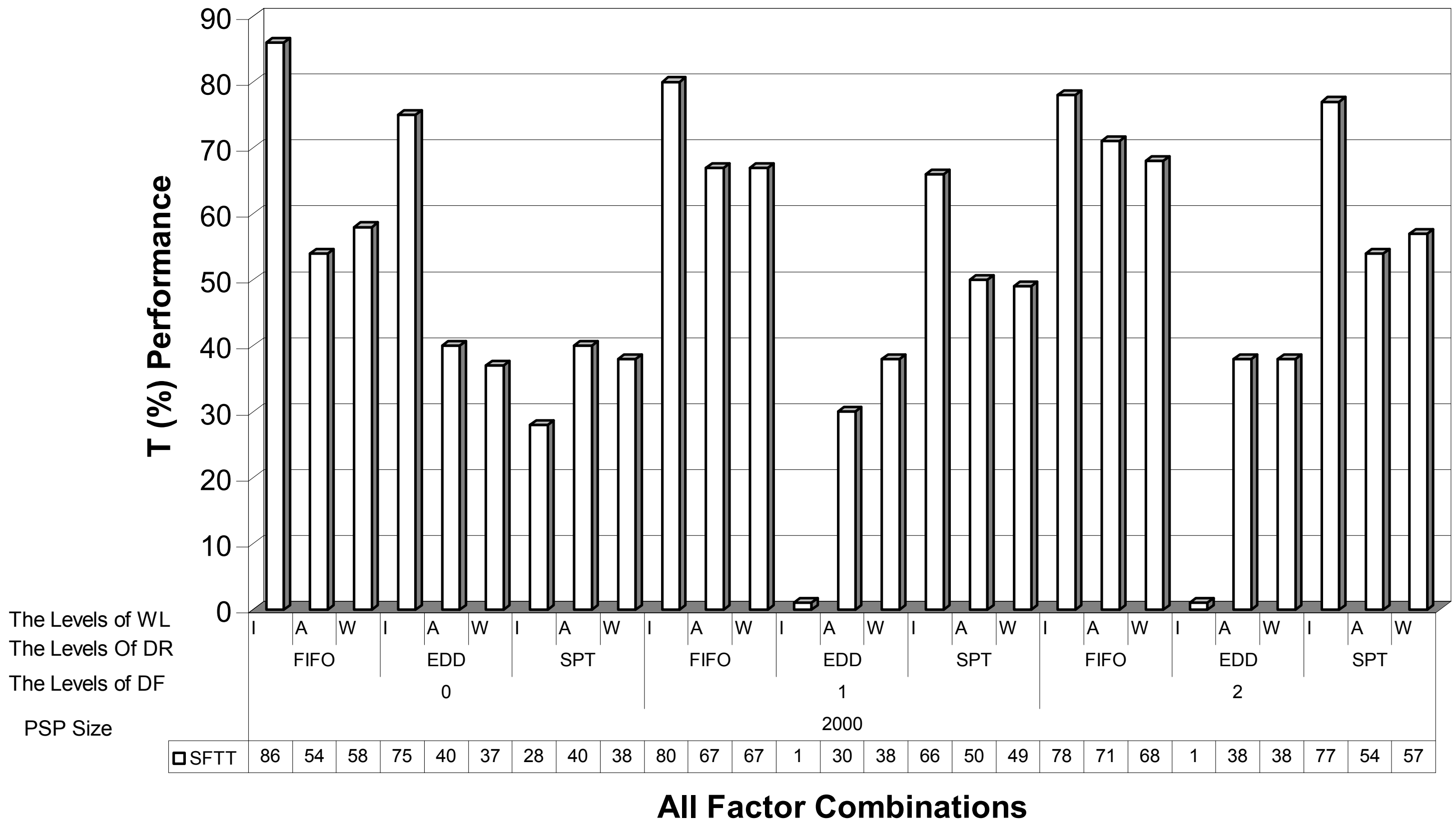


Figure B.20. T (%) with OR mechanisms (PSP Size: 2000)

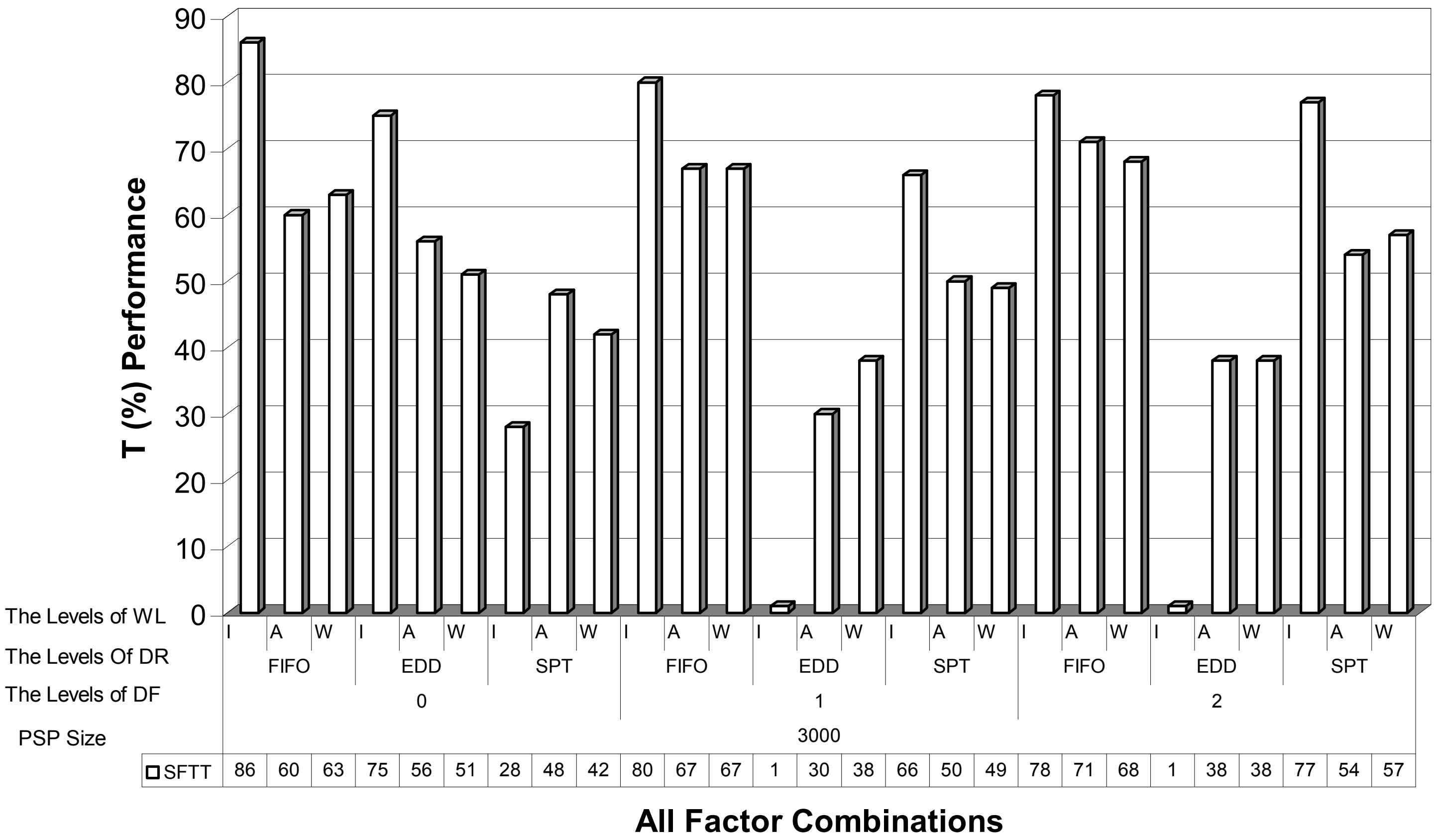


Figure B.21. T (%) with OR mechanisms (PSP Size: 3000)

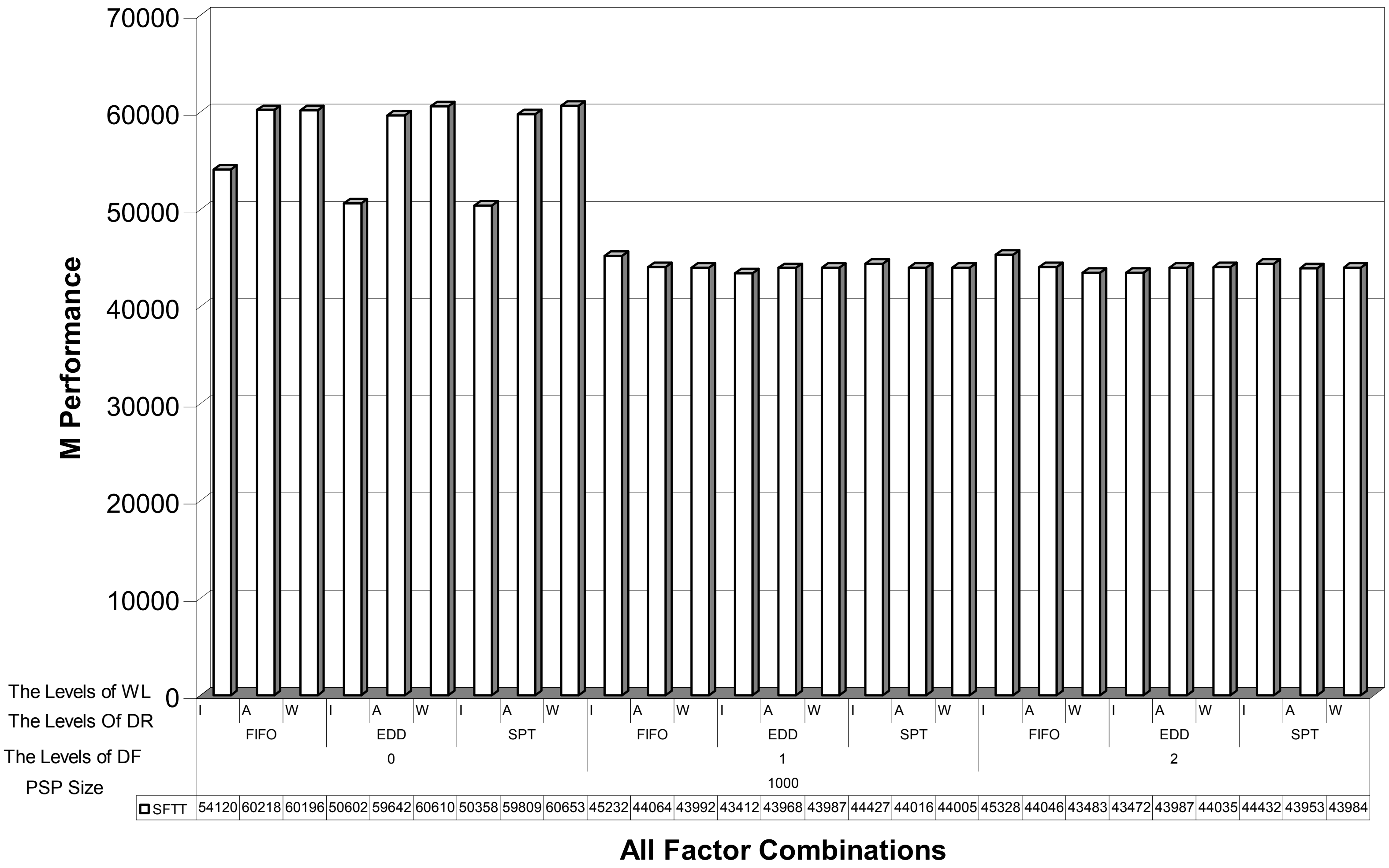


Figure B.22. M with OR mechanisms (PSP Size: 1000)

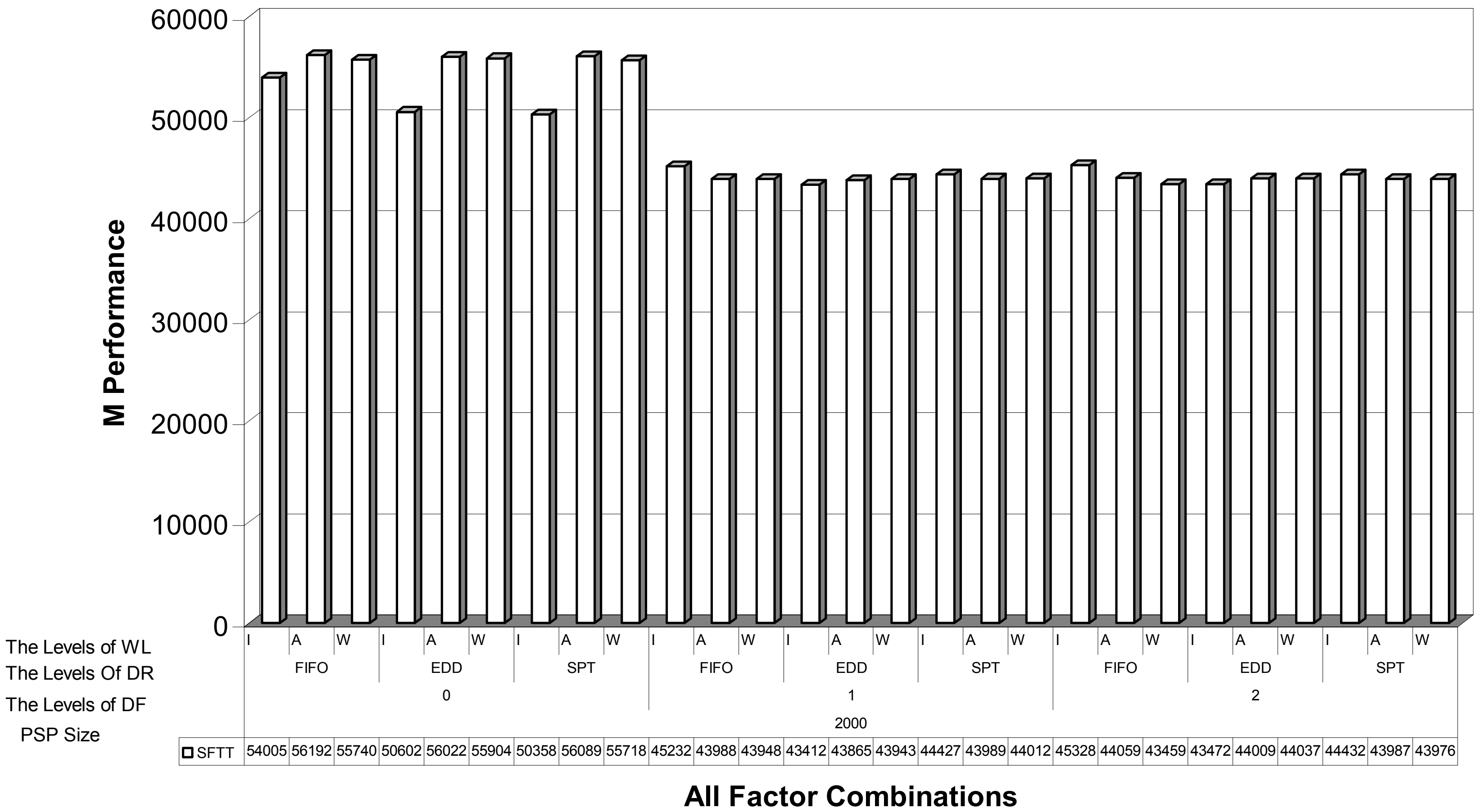
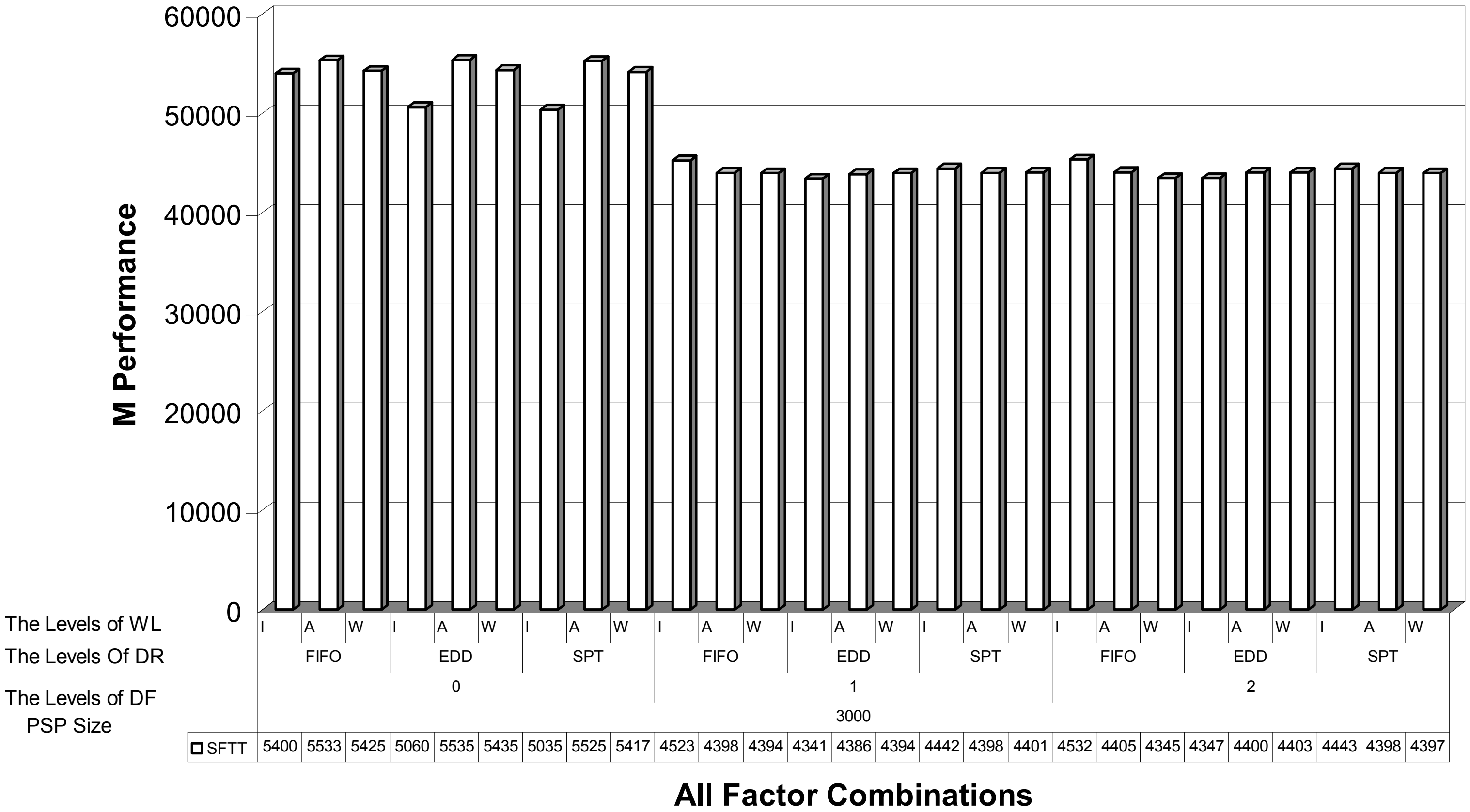


Figure B.23. M with OR mechanisms (PSP Size: 2000)



PSP Size	3000																											
The Levels of DF	0									1									2									
The Levels Of DR	FIFO			EDD			SPT			FIFO			EDD			SPT			FIFO			EDD			SPT			
The Levels of WL	I	A	W	I	A	W	I	A	W	I	A	W	I	A	W	I	A	W	I	A	W	I	A	W	I	A	W	
SFTT	5400	5533	5425	5060	5535	5435	5035	5525	5417	4523	4398	4394	4341	4386	4394	4442	4398	4401	4532	4405	4345	4347	4400	4403	4443	4398	4397	

Figure B.24. M with OR mechanisms (PSP Size: 3000)

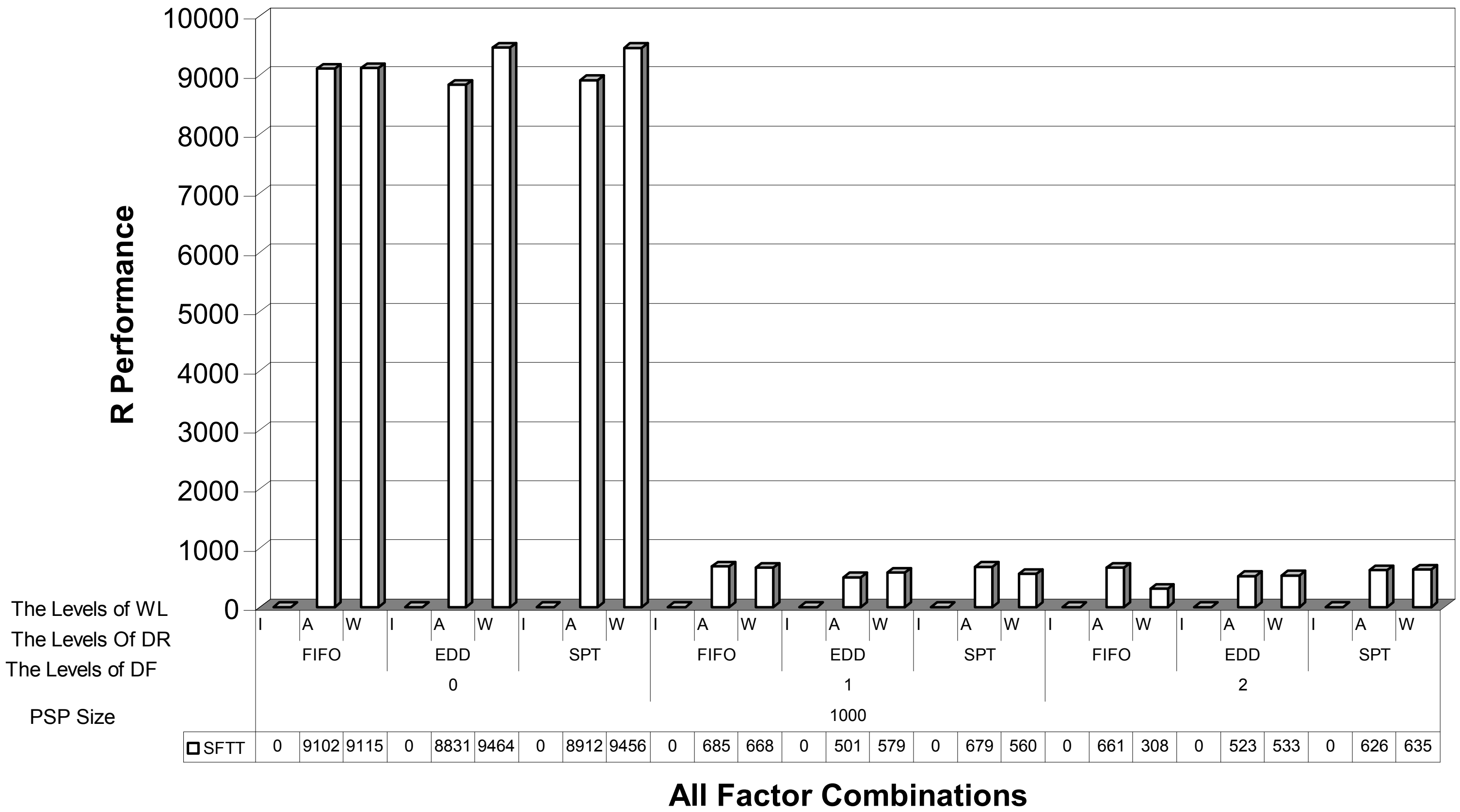


Figure B.25. R with OR mechanisms (PSP Size: 1000)

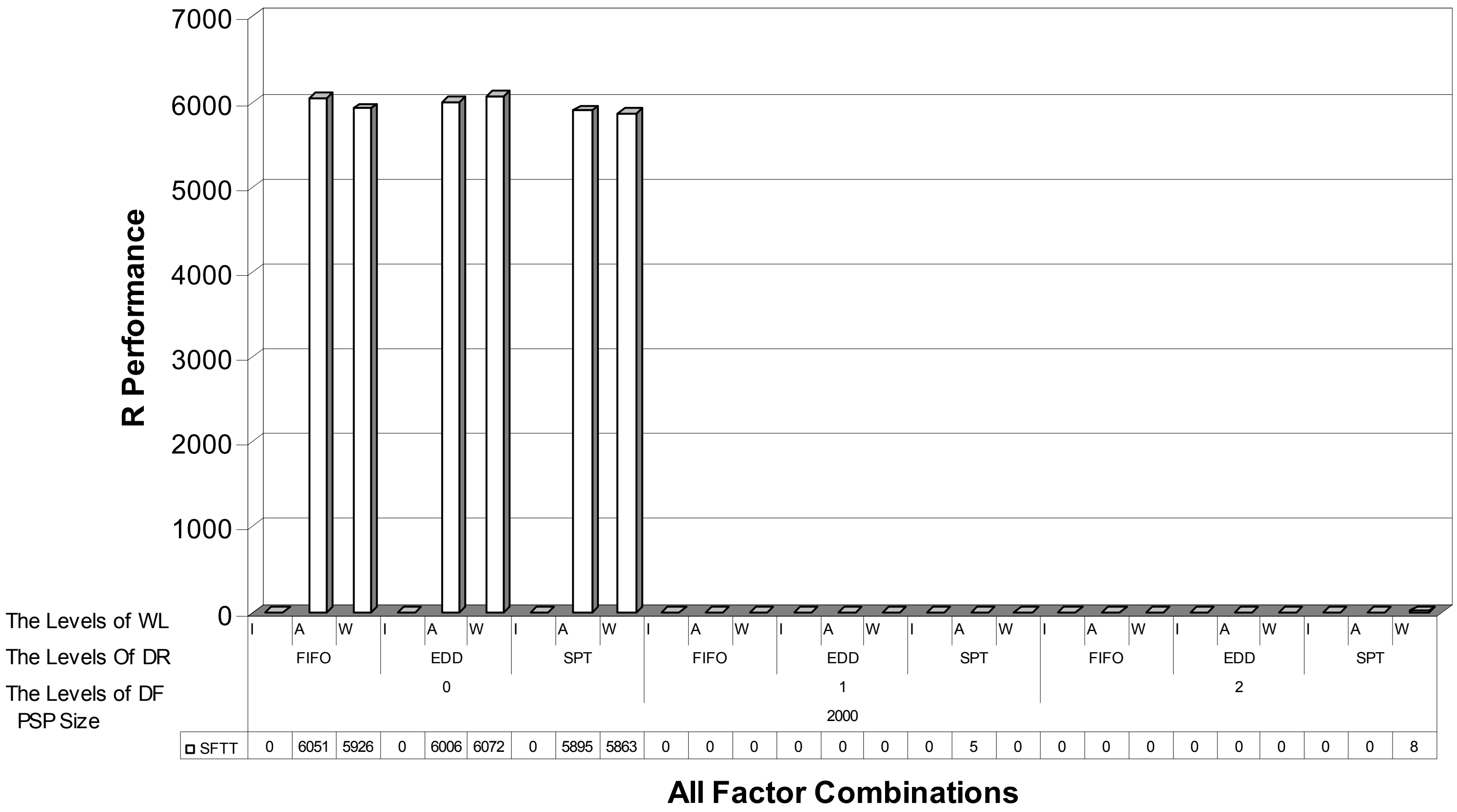


Figure B.26. R with OR mechanisms (PSP Size: 2000)

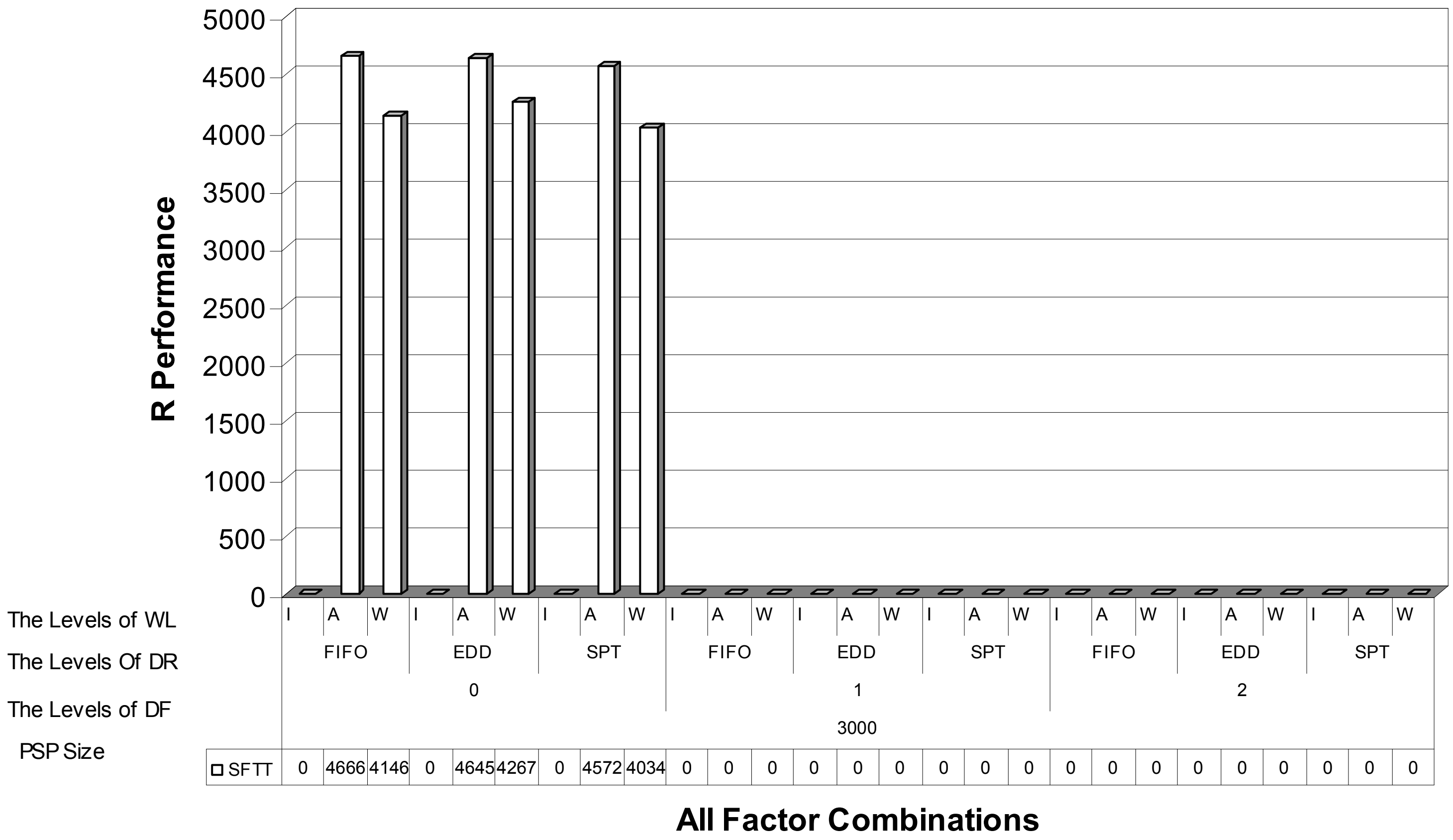


Figure B.27. R with OR mechanisms (PSP Size: 3000)

CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: GÖÇKEN, Mustafa
Nationality: Turkish (TC)
Date and Place of Birth: 12 June 1976 , Kahramanmaraş
Marital Status: Married
Phone: +90 342 317 26 11
Fax: +90 342 360 43 83
email: mgocken@gantep.edu.tr

EDUCATION

Degree	Institution	Year of Graduation
MS	Çukurova University The Graduate School of Natural and Applied Sciences Department of Industrial Engineering	2003
BS	Çukurova University Faculty of Engineering and Architecture Department of Industrial Engineering	1999
High School	Çukurova Elektrik Kahramanmaraş Anatolian High School	1994

WORK EXPERIENCE

Year	Place	Enrollment
2000- 2004	Çukurova University Department of Industrial Engineering	Research Assistant
2004- Present	University of Gaziantep Department of Industrial Engineering	Instructor

FOREIGN LANGUAGES

English

PUBLICATIONS

International Journal Papers

1. Baykasoğlu, A., Göçken, M., Unutmaz, Z.D., New approaches to due date assignment in job shops, European Journal of Operational Research, 187, 31-45, 2008.

2. Baykasoğlu, A., Göçken, M., Unutmaz, Z.D., Due date assignment using ADRES and simulated anealing, International Journal of Industrial and Systems Engineering, 3(3), 277-297, 2008.

Book Chapters

Baykasoğlu, A., Göçken, M., Özbakır, L., Kulluk, S., Composite dispatching rule generation through data mining in a simulated job shop, Modelling, Computation and Optimization in Information Systems and Management Sciences, Second International Conference MCO 2008, Metz, France - Luxembourg, September 8-10, 2008, Hoai An, Le Thi; Bouvry, Pascal; Pham Dinh, Tao (Eds.), ISBN: 978-3-540-87476-8, Springer, Communications in Computer and Information Science , Vol. 14, p. 389-398.

International Conference Papers

1. Baykasoglu A., Dereli T., Göçken M., Flow time estimation using data mining, ICAM'2005 International Conference on Agile Manufacturing, pp.77-81, 27-28 July 2005, Helsinki, Finland, 2005.

2. Baykasoğlu, A., Göçken, M., Testing the performance of capability based distributed layout using simulation, AMSE'06: International Conference on Modelling and Simulation, 28-30 August 2006, pp. 983-987, Konya, Turkey.

3. Baykasoğlu A., Göçken M., Simulation based due-date assignment via gene expression programming, 8th EUMEeting on Metaheuristics in the Service Industry, Stuttgart, Germany, 04-05 October, 2007.

4. Baykasoğlu A., Göçken M., Özbakır L., A data mining approach to dispatching rule selection in a simulated job shop, 8th EUMEeting on Metaheuristics in the Service Industry, Stuttgart, Germany, 04-05 October, 2007.

National Conference Papers

1. Erol R., Göçken M., Bilgisayar Destekli Üretim Kontrol Sistemlerinde Veri Madenciliği (Data Mining) Teknikleri, YA/EM'01: Yöneylem Araştırması ve Endüstri Mühendisliği Kongresi XXII. Ulusal Kongresi Bildiri Özetleri, Ankara, pp. 44-45, 2001.

2. Erol R., Göçken M., Atölye Tipi Üretim Sistemlerinde Akış Süresi ve Teslim Tarihi Belirlenmesinde Zaman Serileri Yaklaşımı, TAINN'2003, International Twelfth Turkish Symposium on Artificial Intelligence and Neural Networks, 02-04, July, 2003, Çanakkale, Turkey, Paper Code T09013, 2003.

3. Baykasoğlu, A., Göçken, M., Unutmaz, Z. D., Atölye tipi üretimde akış süresi tahmini ve teslim tarihi belirlenmesi için yeni bir yaklaşım, GAP V. Mühendislik Kongresi, 26-28 Nisan 2006, Şanlıurfa.

4. Baykasoğlu, A., Göçken, M., Unutmaz, Z.D., Atölye tipi üretim sisteminde girdi kontrolü etkilerinin araştırılması, YA/EM 2007: Yöneylem Araştırması ve Endüstri Mühendisliği 27. Ulusal Kongresi, 02-04 Temmuz 2007, İzmir, 698-703.

5. Baykasoğlu, A., Göçken, M., Unutmaz, D.Z., Benzetim ve diferansiyel evrim algoritması ile çok aşamalı atölyelerde teslim tarihi atama, ÜAS'2007: Ulusal Üretim Araştırmaları Sempozyumu, Gazi Üniversitesi, 15-17 Kasım 2007, Ankara.