FLOWTIME ESTIMATION IN DYNAMIC JOB SHOPS

A THESIS
SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING
AND THE INSTITUTE OF ENGINEERING AND SCIENCES
OF BILKENT UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
MASTER OF SCIENCE

by
Abdullah Çömlekçi
September, 1996

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I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

FLOWTIME ESTIMATION IN DYNAMIC JOB SHOPS

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M.S. in Industrial Engineering
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September, 1996

In the scheduling literature, estimation of job flowtimes has always been an important issue since the late sixties. The previous studies focus on the problem in the context of due date assignment and develop methods using aggregate information in the estimation process. In this study, we propose a new method which utilizes the job, shop and route information on an operational basis. The performance of the proposed method is measured using a simulation model. It is also compared with the existing methods for a wide variety of performance measures under various experimental conditions.

Key Words: Flowtime Estimation, Due Date Assignment, Simulation, Job Shop Scheduling

ÖZET

DİNAMİK İŞ ATÖLYELERİNDE AKIŞ ZAMANI TAHMİNİ

Abdullah Çömlekçi
Endüstri Mühendisliği Bölümü Yüksek Lisans
Tez Yöneticisi: Doç. Dr. İhsan Sabuncuoğlu
Eylül, 1996

Akış zamanları tahmini, altmışlı yıllardan bu yana çizelgeleme literatüründe önemli bir konu olagelmiştir. Geçmiş çalışmalar, genellikle, teslim zamanı belirlenmesi kapsamında konuya eğilmişler ve bütünsel bilgiler kullanarak metodlar önermişlerdir. Bu tezde, iş, atölye ve rota bilgilerini işin operasyonları bazında ayrıştıran yeni bir akış zamanı tahmin metodu önerilmektedir. Önerilen metodun performansı bir benzetim modeli ile ölçülmekte ve diğer varolan metodlarla birçok performans kriterine göre ve birçok deneysel ortamda karşılaştırılmaktadır.

Anahtar Sözcükler: Akış Zamanı Tahmini, Teslim Zamanı Belirlenmesi, Benzetim, İş Atölyeleri Çizelgelemesi

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Chapter 1

Introduction

In the job shop scheduling literature, estimation of job flowtimes has always been an important issue since the late sixties. However, the problem has been identified mostly within the context of due date assignment. This is due to the fact that flowtime estimation is critically important when assigning due dates to be promised to the customers. Beyond the objective of due date assignment, quality of flowtime estimates also leads to significant improvements in the shop floor control activities, such as order review/release, evaluation of the shop performances, identification of jobs that require expediting, etc.

The research problem studied in this thesis is the estimation of the time spent by the jobs in the system from their arrival until the completion of all its processing activities. The difficulty of the problem comes from the dynamic and stochastic nature of the job shop environments (i.e. arrival of hot jobs, sudden machine breakdowns and variations in machining conditions, etc.)

The studies in the literature approach to the problem by identifying the key information sources required in flowtime estimation. As a result, job, shop and route information are outlined as the major elements in the developed estimation methods. Among them, route is reported and used as the most valuable information source.

In the previous studies, researchers use the above information sources in aggregate terms and thus ignore the benefits of using the detailed shop and route congestion information for flowtime estimation.

In this study, we develop a new method which estimates operational flowtimes in dynamic job shop environments. The proposed method utilizes job, shop and route information and exploits these information on the operational basis. The machine imbalance and dispatching rule information are also considered.

The rest of this thesis is organized as follows. In Chapter 2, we present the literature for both the analytical and the simulation approaches. In Chapter 3, basic structure and characteristics of the proposed flowtime estimation method are described. The key components of the model are reviewed via an illustrative example. In Chapter 4, we define the experimental design and the details of our simulation model. In Chapter 5, the results of the simulation experiments are discussed with the applications of appropriate statistical procedures. Finally, the concluding remarks are made and further research directions are outlined in Chapter 6.

Chapter 2

Literature Review

2.1 Introduction

Due date assignment is one of the main application areas of flowtime estimation. As it is frequently observed in the literature, most of the research efforts directed to the flowtime estimation take place within the context of due date assignment (Eilon and Hodgson [11], Eilon and Chowdhury [10], Taylor and Moore [31]). This evolves from the fact that due date setting procedures require flowtime estimation methods as a support tool. In this chapter, we will discuss the due date assignment literature to the extent that flowtime estimation efforts exist for dynamic systems. This means that we will not discuss the studies conducted for static systems nor the studies that calculates due dates for dynamic systems based on predetermined tightness factors.

The literature on flowtime estimation is comprised of mainly two approaches : analytical approach and simulation approach. Cheng and Gupta [8] provides an extensive survey of both approaches in due date assignment. He also gives a framework for scheduling problems consisting of the due date determination process.

The dynamic and stochastic nature of production systems usually renders the development of sophisticated analytical models. Consequently, restrictive assumptions are made in order to obtain some feasible solutions. But these assumptions prevent the application of analytical models in real life situations. Thus, in many cases, simulation seems to be the sole feasible way of handling such complex systems in flowtime estimation. However, simulation approach may not always lead to reliable estimates. Moreover, in striving for the accurate and precise estimates, a great number of computer runs may be required. In conclusion, there is a trade-off between the analytical and simulation approaches which in turn leads to the development of literature in both directions. As our primary concern is on simulation approach we will mainly focus on the simulation side of the literature.

In the rest of this chapter, we will first briefly summarize the analytical studies and then discuss the research works which are primarily based on simulation approach.

2.2 Analytical Approach

Flowtime estimation can be also seen as a key component of scheduling systems. In such a study, Miyazaki [21] proposes a scheduling system to reduce job tardiness by combining a due date assignment procedure with a sequencing procedure. He derives formulae to obtain the mean and the standard deviation of job flowtimes. Number of machines, ratio of the load to the production capacity and the machine utilization information are used in estimating mean and the standard deviation of flowtimes. With the help of the formulae and an adjustment factor, due dates are assigned to the jobs. The new combined approach performs better than the conventional scheduling systems. However, the performance of the proposed flowtime estimation method is not measured separately.

Although Miyazaki's first formula determines the mean of the job flowtimes exactly, his second formula approximates the standard deviation. Cheng [3] extends Miyazaki's work and derives both the mean and the standard deviation of the job flowtimes exactly by using Laplace transforms method. The robustness of results to the violation of the assumption of equality of the mean processing times of the machines in the shop is also examined and it is found to be robust.

Enns [12] extends the works of Miyazaki [21] and Cheng [3] and proposes four analytical flowtime assignment methods each using combinations of job and shop information. He compares these methods with respect to many performance criteria and reaches the conclusion that both shop and job information are useful in estimating flowtimes. Another important finding of this study is that as the accuracy and precision of the estimates improve, the lateness distribution becomes to be normally distributed. However, the proposed methods are only valid when the dispatching rule is first-come-first-served (FCFS).

Cheng [4] presents another analytical model that can determine the optimal coefficients for TWK (Total Work Content) and TWK-NOP (Total Work Content and Number of Operations) rules (see Section 2.3 for the definitions of these rules). However, the proposed model is based on some restrictive assumptions on queue discipline and processing time distribution. The analytical results are compared with the simulation results and validated through the observations that the results agree with each other. Cheng [4] also claims that TWK-NOP is more effective in minimizing missed due dates costs in a job shop. Cheng [7] elaborates more on the determination of coefficients for TWK for an assembly shop. A critical path based analysis of the job processes information is developed to obtain the coefficient value for TWK that minimizes the expected value of the squared lateness. A formula which approximates the optimal coefficient value is derived and it is shown that the approximation error is below 30 per cent in the worst case situation. It is also shown that that the proposed method is effective for jobs with varying structural complexities.

Cheng [5] proposes another method of assigning optimal due dates and a heuristic approach which minimize the average amount of missed due dates in a single machine shop with the queue discipline of SPT. He evaluates the analytical results by comparing with the simulation results for various shop conditions and concludes that the heuristic method can produce accurate due dates effectively.

Shanthikumar and Buzacott [28], [29] model a dynamic job shop as the open queuing network and derives approximations to the mean and the standard deviation of flowtimes. However, their model produces effective approximations only for the job shops with local dispatching rules. Buzacott and Shanthikumar [2] show that the mean and standard deviation of the flowtimes are smaller for SPT when compared with the FCFS dispatching rule. Shanthikumar and Sumita [30] extend this study and develop approximations to the distribution of the flowtimes. They also use these distributions in controlling the total costs incurred for tardiness and earliness of the jobs while assigning due dates.

Finally, Lawrence [20] proposes a due setting methodology for which the flowtime error distributions are approximated empirically by Ramberg-Schmeiser [26] distributions. Using the properties of Ramberg-Schmeiser distributions, the best due dates are obtained for different objectives such as minimizing mean squared lateness, minimizing total tardiness and earliness costs and attainment of some service level targets.

2.3 Simulation Approach

One of the early works in the simulation approach has been conducted by Conway [9]. In this study, four flowtime estimation methods are compared: Total Work Content (TWK), Number of Operations (NOP), Constant (CON), Random (RDM). The mathematical definitions of these methods are as follows :

$$\begin{array}{llcl} TWK: & F_i & = & kP_i \\ NOP: & F_i & = & kN_i \\ CON: & F_i & = & K \\ RDM: & F_i & = & kX_i \end{array}$$

where,

$$\begin{array}{lcl} F_i & = & \text{Flowtime estimate of job } i \\ P_i & = & \text{Total processing time of job } i \\ N_i & = & \text{Number of operations of job } i \\ X_i & = & \text{A random number assigned for job } i \\ k, K & = & \text{constants} \end{array}$$

These methods are used in assigning the due dates. The results of his simulation experiments indicates that the methods which utilizes the job information perform better than the ones that do not consider. Conway [9] also reports that there exists a relationship between the due date assignment methods and the dispatching rules.

Eilon and Hodgson [11] compare the performances of dispatching rules when due dates are assigned by TWK method. It appears that SPT is the best dispatching rule with respect to several performance measures such as waiting times, queue lengths, etc. In this study, the best k_1 values which minimizes the total penalty costs for earliness or tardiness are also obtained. This study is also the first simulation study which aims at finding the best coefficient values.

Eilon and Chowdhury [10] first uses shop congestion information in estimating flowtimes. In this study, TWK is compared with three new methods which are all extensions of TWK: Jobs in Queue (JIQ), Delay in Queue (DIQ), Modified Total Work Content (MTWK). The mathematical forms of these methods are:

$$\begin{aligned} DIQ: \quad & F_i = k_1 P_i + k_2 W \\ JIQ: \quad & F_i = k_1 P_i + k_2 Q_i \\ MTWK: \quad & F_i = k_1 P_i^{k_2} \end{aligned}$$

where,

W = Mean waiting time per job.

Q_i = Number of jobs in progress along the route of job i.

k_1, k_2 = constants

Results indicate that JIQ method, which employs the shop congestion information, outperforms all other methods. JIQ also produces better results than the other methods for a shop with fluctuating load ratio. This is because, the other methods do not make use of the shop load information. Another observation of this study is that due date dependent dispatching rules provide better results in terms of missed due dates as compared to the due date independent dispatching rules.

Weeks [34] proposes a method which also combines job and shop information:

$$F_i = max(P_i + W + I(TQ_i)\sigma_W, P_i)$$

where,

TQ_i= Total number of jobs in the system when job i arrives.

$$I(TQ_i) = \begin{cases} 1 & \text{if } TQ_i \leq TQ - \sigma_{TQ} \\ 0 & \text{if } TQ_i - \sigma_{TQ} < TQ_i < TQ + \sigma_{TQ} \\ -1 & \text{if } TQ_i \geq TQ + \sigma_{TQ} \end{cases}$$

TQ= Mean number of jobs in the system.

σ_{TQ}= Standard deviation of number of jobs in system.

σ_W= Standard deviation of waiting times of jobs.

This method is found to be superior over the previously proposed methods for the performance measures such as mean lateness, mean earliness, and mean missed due dates. Three different types of production systems are also investigated in the study and it is empirically shown that, as the structural complexity of the shop is increased, the performances of the methods are negatively affected. It is also reported that the performances are not much influenced from the shop size. It is noted that shop size is being characterized by the number of machines and workcenters in the shop whereas the shop complexity is characterized only by the increased structural departmentation (divisions in the shop).

Taylor and Moore [31] demonstrate the use of network modeling and simulation in estimating job flowtimes for a job shop. They present their approach via an example and show how a job shop can be modeled as a network with the Q-GERT technique. They also emphasize that the practical benefits that may be achieved by network modeling.

Bertrand [1] proposes a new method of flowtime estimation which exploits time-phased workload information of the shop:

$$F_i = P_i + P \times SL \times N_i + F_i(W_t)$$

where,

P	=	Mean processing time in the shop
SL	=	Minimum allowance for waiting
$F_i(W_t)$	=	Additional flow time allowance, dependent in observed congestion due to the workload, W_t, in the shop

Two factors are used in analyzing the performance of the method: SL and CLL (capacity loading limit). The method is compared with its version that does not take into account the time-phased workload information (i.e. $F_i(W_t)$

is omitted from the model). It is seen that time-phased workload and capacity information significantly decreases variance of the lateness.

Ragatz and Mabert [25] give an extensive comparison of eight different methods and evaluate their performances for a hypothetical job shop with respect to three performance measures: mean tardiness, mean absolute lateness and standard deviation of lateness. TWK, NOP, TWK-NOP, JIQ, WIQ (similar to JIQ except that the total processing times of jobs on the route is used instead of the number of them), WEEK's method, JIS (similar to JIQ except that the number of jobs at the system is used instead of the number of jobs on the route), and RMR (Response Mapping Rule) are compared with this study.

RMR is the proposed method in the study, and it utilizes the response surface mapping procedures to identify the significant factors in estimation of the flowtimes. Three different models are constructed for each dispatching rule used in the analysis. This is needed because different factors appear to be significant for each dispatching rule.

An interesting result of this study is the poor performance of WEEK's method with respect to most of the other flowtime estimation methods. It is also reconfirmed by this study that both shop and job information are useful in flowtime estimation. Another observation of the study is that the workload information along the route is more useful than the general shop information. It is also reported that the use of more detailed information with RMR does not improve the performance much over the other methods that use more aggregate information.

Cheng [6] exploits a hypothetical job shop to determine the main and interaction effects of: due date assignment method, dispatching rule, and shop load ratio. He employs multiple regression analysis on the results to estimate the mathematical relations between these three factors and the performance measure of percentage late jobs. The derived regression model is used to obtain percentage of late jobs for any given shop conditions characterized by the three factors.

Kanet and Christy [17] compare TWK with the Processing Plus Waiting (PPW) method for a general job shop with forbidden early shipment of completed jobs. PPW method estimates a job's flow allowance by adding an estimate of the waiting time, which is proportional with the number of operations, to the total processing time of a job. The experimental results showed that TWK is superior to PPW in terms of the performance measures of mean tardiness, proportion of tardy jobs, and mean inventory levels.

Fry, Philipoom and Markland [15] investigate the job and shop characteristics which affect a job's flowtime in a multistage job shop. The characteristics they have identified are:

a) Job Factors

- Sum of all operation times in the BOM.
- Sum of all operation times on the critical path of the BOM
- Total number of assembly points in the BOM
- Number of branches or components in the BOM

b) Shop Factor

- Total amount of work in the system

With these factors, they construct two linear and two multiplicative nonlinear models and estimate the coefficients of the factors via regression analysis. The following conclusions are drawn from this study:

a) Models using product structure and shop conditions can estimate flowtimes better than the others.

b) Linear models are superior to the multiplicative models.

c) As utilization increases, the predictive ability of the models also increase.

Vig and Dooley [32] propose two new flowtime estimation methods which utilize flowtime per operation information of the recently finished jobs: Operation Flowtime Sampling (OFS) and Congestion and Operation Flowtime Sampling (COFS). The mathematical forms of these methods are:

$$\begin{aligned} \textit{OFS}: \quad & F_i = k_1 T_i + k_2 N_i + k_3 P_i \\ \textit{COFS}: \quad & F_i = k_1 T_i + k_2 Q_i + k_3 N_i + k_4 P_i \end{aligned}$$

where,

T_i	=	$A \times N_i$
A	=	$A_1/NR_1 + A_2/NR_2 + A_3/NR_3$
A_1, A_2, A_3	=	Flowtimes of the three most recently completed jobs
NR_1, NR_2, NR_3	=	Number of operations of the three most recently completed jobs

These methods are compared with JIQ and TWK-NOP methods under various shop conditions. The results show that COFS and JIQ methods give the overall best performances, but OFS method shows also good performance when MOD dispatching rule is used. The interactions of the experimental factors are also analyzed through analysis of variance. It is observed that flowtime estimation method, dispatching rule, and shop balance all influences the performance of the shop for all performance measures. Vig and Dooley [33] extend this work by combining static and dynamic estimates to obtain job flowtime estimates with the following method:

$$F_i = (1 - \alpha)F_{st} + \alpha F_{di}$$

where,

α = Weighting factor

F_{st} = Static flowtime estimate (mean flowtime)

F_{di} = Dynamic flowtime estimate of job i

In this method, the dynamic estimates are produced by COFS and OFS methods. With the data collected from steady state simulation runs, the actual and dynamic flowtime estimates are compared one by one and a range for the weighting factor α is obtained. The α value to be implemented is selected from this range.

Vig and Dooley [32] and [33] also investigate the effect of the shop balance on the performance of the flowtime methods and they conclude that the balance information significantly affects the performance of the flowtime estimation methods.

Gee and Smith [16] propose an iterative procedure for estimating flowtimes when due date dependent dispatching rules are used. Two flowtime estimation methods using local (job related) information and global (both job and shop related) information are also employed to present the benefits of iterative estimation.

Local Method:

$$F_i = k_1 P_i + k_2 N_i + k_3 P_i^2 + k_4 N_i^2$$

Global Method:

$$F_i = k_1 P_i + k_2 R_i + k_3 S_i + k_4 P_i^2 + k_5 R_i^2$$

where,

R_i = Total processing time for operations in queue along the routing of job i

S_i = Total processing time for operations elsewhere in the shop that require machines that are required by job i

It is reported that the global rule gives better estimation performance most of the time. It is interesting to note that the load information out of the route, (S_i), is valuable in estimation of the flowtimes.

The impact of the iterative approach is demonstrated also by comparing the second method with the RMR approach previously proposed by Ragatz and Mabert [25]. The experimental results show that using the iterative approach for due date dependent dispatching rules improves the performance of the flowtime estimation methods. This is because, the regression equations fitted for a method, change at each iteration. Since due dates are based on the flowtime estimates, the dispatching in the shop is also changed at each iteration.

Enns [13], [14] describes a dynamic estimation method which employs a dynamic version of the PPW method. By using exponentially smoothed flowtime estimation error feedback, the operation lateness variance is estimated and used when setting due dates for jobs. It is shown in this study that the estimation errors are normally distributed. By making use of this observation, they describe a method of setting due dates that enables the achievement of the desired percentage of tardy jobs so that the delivery performance is controlled. It is also reported that the due date dependent dispatching rules lead to better performance as compared to due date independent rules.

Kaplan and Unal [18] suggest a cost based approach for determining the due dates. The proposed approach states that the due dates are calculated by summing the flowtime estimate with a multiple of the estimated standard deviation of the flowtime estimation error. Their analysis is composed of two stages. In the first stage, a flowtime estimation model is derived. By performing a correlation analysis over the shop, job and route related factors, the key factors affecting the shop are determined. Several models are developed for each combination of these factors and one of the models is selected to be used in the due date assignment procedure. In the second stage, the coefficient to be used when adding a multiple of the standard deviation of estimation error, is sought. This coefficient is obtained by optimizing the total cost (holding cost plus tardiness cost) function. They also consider the balance of the shop in their experimental study.

In the literature, applying multiple regression to the data collected via simulation experiments is a commonly used procedure for flowtime estimation. Philipoom, Rees and Wiegmann [24] present the use of neural networks as an alternative to this approach. In their study, they estimate the coefficients of the methods previously tested by Ragatz and Mabert [25] with neural networks instead of multiple regression. It is observed that the neural network approach outperforms the conventional regression based approach in two of the three shops tested in their study.

2.4 Conclusion

From the literature review, we make the following observations:

- The interactions between the flowtime estimation methods and the dispatching rules are significant. Hence, the dispatching rule used in a system influences both the shop performance and the performance of the flowtime estimation method ([6], [8], [9], [11], [12], [21], [25]).
- Both shop and job characteristics are important for estimation of flowtimes ([1], [3], [10], [12], [21], [25], [32], [33], [34]).
- Splitting the shop congestion information as the load on the route and the load out of the route enhances predictive power of the flowtime estimation methods. Especially, the load information along the route of a job is seen to be more useful than the other general shop information ([10], [25], [32], [33]).

- Due date dependent dispatching rules provide superior shop performance over the due date independent rules ([10], [14]).
- Shop balance information significantly affects the performance of the flowtime estimation methods ([18], [32], [33]).
- Use of aggregate information leads to almost the same performance when compared with the use of more detailed information with RMR ([25]).

In the rest of this thesis, we will evaluate the problem of estimation of flowtimes by taking into account these observations and will propose a new flowtime estimation method.

Chapter 3

Proposed Method

In this chapter, we describe the basic structure and characteristics of the proposed flowtime estimation method.

3.1 Motivating Points

In this section, we outline the main ideas which motivated us to develop a new flowtime estimation model.

1) Previous research indicated that total load on the process route of an arriving job provides valuable information in flowtime estimation. (Eilon and Chowdhury [10], Bertrand [1], Ragatz and Mabert [25], Vig and Dooley [32], [33]) Moreover, we expect that distribution of this load on the machines along the route of the job is also as important as the total load itself. As one can intuitively expect, the existing load of the machine close to the beginning of the route of the job would affect the flowtime of that job more than the load close to the end of the route. Because state of the system could be quite different when the job arrives at the machines for later operations. Thus, splitting the route information with respect to operations of the job can improve the performance of a flowtime

estimation method.

2) Previous research has also indicated that consideration of total loads of the jobs elsewhere in the shop (i.e. the jobs which are not currently at the respective machines on the route of the arriving job, but will visit these machines later in their processes) is also important (Gee and Smith [16]). Because these jobs will eventually bring additional loads to the route of the arriving job. Hence, both timing and distribution of these so called "other jobs" should also be considered in flowtime estimations.

3) Many researchers have demonstrated that dispatching rules used to sequence jobs also affect the performance of estimation methods ([6], [8], [9], [11], [12], [21], [25]). For example, Ragatz and Mabert [25] investigated this situation and proposed different flowtime estimation models for different dispatching rules in their proposed "Response Mapping Rule (RMR)".

   In our study, we also use different dispatching rules for flowtime estimation. But the use of dispatching rule information in our case is quite different than the usage in the literature; instead of using a separate prediction model for each rule, we use the same model but redefine the variables for each dispatching rule. For example, when total load is used as a variable in the model, the total operation times of all the jobs in the queue is calculated for FCFS rule whereas the total operation time of the jobs with smaller operation times than the arriving job is used for the SPT rule. Thus, meanings of the variables in our model are quite different for different dispatching rules.

4) It has been also shown in the literature that the performance of the flowtime estimation methods are significantly affected as the balance of the shop deteriorates. Bertrand [1] uses the time-phased profile of the workload information and implicitly considers the shop balance in his proposed model. However, there is currently no study in the literature which explicitly considers machine imbalance information in flowtime estimation. In our study, however, we will consider explicitly the long run load information for each machine.

3.2 Model

In this section, we describe the basic characteristics and structure of the proposed flowtime estimation model whose motivating points are outlined in the previous section. In the model, the following variables are considered:

a) the processing time of the job,

b) the existing total load of the machine on which the job will be processed, and

c) the total load that will soon arrive to the machine on which the job will be processed.

These variables have been selected because they capture most of the operational information of a job. The generic model is as follows:

$$PF_{ji}^{k} = c_{1j}^{k} X_{1ji}^{k} + c_{2j}^{k} X_{2ji}^{k} + c_{3j}^{k} X_{3ji}^{k} \qquad (1.1)$$

where,

PF_{ji}^{k} : Partial flowtime of job i for its kth operation at machine j

X_{1ji}^{k} : Sum of processing times of the *relevant jobs*[1] at the queue of machine j that job i will have its kth operation

X_{2ji}^{k} : Sum of processing times (on the machine j that job i will have its kth operation) of the *relevant jobs*[1] at the queues of the machines other than machine j but require machine j in the future

X_{3ji}^{k} : Processing time of job i at machine j for its kth operation

[1] Only a subset of jobs are used in calculating the values of the variables. These jobs are called the relevant jobs. The criteria for selecting these relevant jobs are given in section 3.2.1.

$c_{1j}^k, c_{2j}^k, c_{3j}^k$: coefficients

When job i arrives to the system, the PF_{ji}^k values are calculated for each operation by using the above equations. Then, the total flowtime estimate F_i is obtained by summing these values.

In the balanced shop case, since the utilizations of the machines are nearly the same, they can be treated as identical machines. Thus, the above model is simplified into:

$$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k \qquad (1.2)$$

where,

PF_i^k : Partial flowtime of job i for its kth operation

X_{1i}^k : Sum of processing times of the *relevant jobs* at the queue of the machine that job i will have its kth operation

X_{2i}^k : Sum of processing times of the *relevant jobs* at the queues of the machines other than the machine that job i will have its kth operation, but will require that machine in the future

X_{3i}^k : Processing time of job i for its kth operation

c_1^k, c_2^k, c_3^k : coefficients

The following equations are obtained for a job shop comprised of 5 machines:

a) Unbalanced shop :

Machine #1

$$PF_{1i}^{1} = c_{11}^{1}X_{11i}^{1} + c_{21}^{1}X_{21i}^{1} + c_{31}^{1}X_{31i}^{1}$$
$$PF_{1i}^{2} = c_{11}^{2}X_{11i}^{2} + c_{21}^{2}X_{21i}^{2} + c_{31}^{2}X_{31i}^{2}$$
$$PF_{1i}^{3} = c_{11}^{3}X_{11i}^{3} + c_{21}^{3}X_{21i}^{3} + c_{31}^{3}X_{31i}^{3}$$
$$PF_{1i}^{4} = c_{11}^{4}X_{11i}^{4} + c_{21}^{4}X_{21i}^{4} + c_{31}^{4}X_{31i}^{4}$$
$$PF_{1i}^{5} = c_{11}^{5}X_{11i}^{5} + c_{21}^{5}X_{21i}^{5} + c_{31}^{5}X_{31i}^{5}$$

Machine #2

$$PF_{2i}^{1} = c_{12}^{1}X_{12i}^{1} + c_{22}^{1}X_{22i}^{1} + c_{32}^{1}X_{32i}^{1}$$
$$PF_{2i}^{2} = c_{12}^{2}X_{12i}^{2} + c_{22}^{2}X_{22i}^{2} + c_{32}^{2}X_{32i}^{2}$$
$$PF_{2i}^{3} = c_{12}^{3}X_{12i}^{3} + c_{22}^{3}X_{22i}^{3} + c_{32}^{3}X_{32i}^{3}$$
$$PF_{2i}^{4} = c_{12}^{4}X_{12i}^{4} + c_{22}^{4}X_{22i}^{4} + c_{32}^{4}X_{32i}^{4}$$
$$PF_{2i}^{5} = c_{12}^{5}X_{12i}^{5} + c_{22}^{5}X_{22i}^{5} + c_{32}^{5}X_{32i}^{5}$$

Machine #3

$$PF_{3i}^{1} = c_{13}^{1}X_{13i}^{1} + c_{23}^{1}X_{23i}^{1} + c_{33}^{1}X_{33i}^{1}$$
$$PF_{3i}^{2} = c_{13}^{2}X_{13i}^{2} + c_{23}^{2}X_{23i}^{2} + c_{33}^{2}X_{33i}^{2}$$
$$PF_{3i}^{3} = c_{13}^{3}X_{13i}^{3} + c_{23}^{3}X_{23i}^{3} + c_{33}^{3}X_{33i}^{3}$$
$$PF_{3i}^{4} = c_{13}^{4}X_{13i}^{4} + c_{23}^{4}X_{23i}^{4} + c_{33}^{4}X_{33i}^{4}$$
$$PF_{3i}^{5} = c_{13}^{5}X_{13i}^{5} + c_{23}^{5}X_{23i}^{5} + c_{33}^{5}X_{33i}^{5}$$

Machine #4

$$PF_{4i}^{1} = c_{14}^{1}X_{14i}^{1} + c_{24}^{1}X_{24i}^{1} + c_{34}^{1}X_{34i}^{1}$$
$$PF_{4i}^{2} = c_{14}^{2}X_{14i}^{2} + c_{24}^{2}X_{24i}^{2} + c_{34}^{2}X_{34i}^{2}$$
$$PF_{4i}^{3} = c_{14}^{3}X_{14i}^{3} + c_{24}^{3}X_{24i}^{3} + c_{34}^{3}X_{34i}^{3}$$
$$PF_{4i}^{4} = c_{14}^{4}X_{14i}^{4} + c_{24}^{4}X_{24i}^{4} + c_{34}^{4}X_{34i}^{4}$$
$$PF_{4i}^{5} = c_{14}^{5}X_{14i}^{5} + c_{24}^{5}X_{24i}^{5} + c_{34}^{5}X_{34i}^{5}$$

Machine #5

$$PF_{5i}^{1} = c_{15}^{1}X_{15i}^{1} + c_{25}^{1}X_{25i}^{1} + c_{35}^{1}X_{35i}^{1}$$
$$PF_{5i}^{2} = c_{15}^{2}X_{15i}^{2} + c_{25}^{2}X_{25i}^{2} + c_{35}^{2}X_{35i}^{2}$$
$$PF_{5i}^{3} = c_{15}^{3}X_{15i}^{3} + c_{25}^{3}X_{25i}^{3} + c_{35}^{3}X_{35i}^{3}$$
$$PF_{5i}^{4} = c_{15}^{4}X_{15i}^{4} + c_{25}^{4}X_{25i}^{4} + c_{35}^{4}X_{35i}^{4}$$
$$PF_{5i}^{5} = c_{15}^{5}X_{15i}^{5} + c_{25}^{5}X_{25i}^{5} + c_{35}^{5}X_{35i}^{5}$$

b) Balanced shop :

$PF_i^1 = c_1^1 X_{1i}^1 + c_2^1 X_{2i}^1 + c_3^1 X_{3i}^1$

$PF_i^2 = c_1^2 X_{1i}^2 + c_2^2 X_{2i}^2 + c_3^2 X_{3i}^2$

$PF_i^3 = c_1^3 X_{1i}^3 + c_2^3 X_{2i}^3 + c_3^3 X_{3i}^3$

$PF_i^4 = c_1^4 X_{1i}^4 + c_2^4 X_{2i}^4 + c_3^4 X_{3i}^4$

$PF_i^5 = c_1^5 X_{1i}^5 + c_2^5 X_{2i}^5 + c_3^5 X_{3i}^5$

3.2.1 Determination of Relevant Jobs

In the proposed method, while calculating the values of X_{1ij} and X_{2ij} for an arriving job i, we do not consider all the jobs in the queues. Instead we focus on some subset of the jobs, and eliminate the rest by using a selection criteria. The jobs that are selected are called "relevant" jobs whereas the others are simply called "irrelevant". Since different sets of jobs are used when calculating the values of X_{1ij} and X_{2ij}, we use different criteria in determining the relevant jobs for each variable.

Determination of Relevant Jobs for X_{1ji}:

The jobs residing at the queue of machine j (the machine on which the arriving job will be processed) are evaluated by the following criteria for each dispatching rule.

FCFS: All of the jobs are selected as "relevant".

SPT: The jobs which have smaller operation times than the arriving job are selected as "relevant".

MOD: Let k be the index for a job waiting at the queue of the machine j and let i be the index for the arriving job.

We calculate two priority indices for each job and select job k as "relevant" if its priority index is lower than the job i's index.

The priority index for job k, I_k, is assigned just as the modified operation due date (see section 4.2.1), whereas the priority index of job i is assigned as the ready time plus a fraction of its total flow allowance. This fraction is calculated by dividing the total processing time required until job i finishes its operation on machine j, by the total processing time required for all of its operations.

Determination of the Relevant Jobs for X_{2ji}:

The jobs residing at the queues of machines other than machine j are evaluated by the following criteria for each dispatching rule.

FCFS: All of the jobs are selected as "relevant".

SPT: The jobs which have smaller operation times than the arriving job are selected as "relevant".

MOD: Let k be the index for a job residing at the queue of a machine other than machine j, and i be the index for the arriving job.

We again calculate two priority indices for each job and select job k as "relevant" if its priority index is lower than that of job i.

The priority index for job i is calculated in the same way as it was calculated for X_{1ji}. The priority index for job k is assigned as a fraction of its remaining flow allowance where this fraction is calculated by dividing the total processing time required until job k finishes its operation on machine j, by the remaining total processing time.

3.3 An Illustrative Example

In this section, we will try to explain the proposed method in more detail via an example.

Let us suppose that job i has just arrived at an unbalanced shop with 5 machines. Assume that this job will visit machine #5, machine #3 and machine #2, for its first, second and third operations, respectively.

The proposed method requires the following equations in order to estimate the flowtime of job i:

$$PF^1_{5i} = c^1_{15}X^1_{15i} + c^1_{25}X^1_{25i} + c^1_{35}X^1_{35i} \quad (1.3)$$

$$PF^2_{3i} = c^2_{13}X^2_{13i} + c^2_{23}X^2_{23i} + c^2_{33}X^2_{33i} \quad (1.4)$$

$$PF^3_{2i} = c^3_{12}X^3_{12i} + c^3_{22}X^3_{22i} + c^3_{32}X^3_{32i} \quad (1.5)$$

When the job arrives to the shop, we collect the values of the $X^k_{.ij}$ variables and plug them into the equations to obtain the partial flowtimes (PFs) for each operation of the job.

The total flowtime of the job i is obtained as follows:

$$F_i = PF^1_{5i} + PF^2_{3i} + PF^3_{2i} \quad (1.6)$$

Notice that if the visitation sequence of the job had been machine #2, machine #3 and machine #5, then the flowtime estimate would have been as follows:

$$F_i = PF^3_{5i} + PF^2_{3i} + PF^1_{2i} \quad (1.7)$$

However, this new flowtime estimate is quite different than the one given before (equation 1.6). Because different PF values are used for different visitation sequences even though the job visits the same set of machines. Hence, it is obvious that the proposed method effectively utilizes the route information. Moreover, the distributions of the loads along the route and outside the route of job i are also captured with the machine and operation specific information provided by the $X^k_{.ij}$ values in the model. Thus, the first and second motivating points given at the beginning of this chapter are well exploited in the proposed method.

Note that the $X^k_{.ij}$ variables can take different values with respect to the dispatching rule implemented in the system. For example, if the dispatching rule is FCFS, X^k_{1ij} becomes the total load of the machine $\#j$. But when the MOD rule is used, the total load is calculated by summing the operation times of the relevant jobs which have earlier modified operation due dates than job i's calculated priority index. This justifies the, third motivating point of the proposed method.

Finally, as one can easily note, machine balance information is directly utilized by the proposed method; the machine indexed coefficients carry the necessary machine load information. The equations for the highly utilized machines are expected to have larger coefficient values that leads to larger partial flowtime estimates. If all the machines have the same utilization, machine indices would not be needed, and hence, the equations would have reduced to the formulation given by (1.2). This property of the proposed method implements our forth motivating point.

3.4 Conclusion

In this chapter, we have presented a new flowtime estimation method, its structure and the motivating points. In the following chapter, we will present the procedure to collect the necessary data and will discuss its computational requirements.

Chapter 4

Experimental Conditions

In this chapter, we discuss the experimental issues related to the flowtime estimation; namely, system considerations and simulation model, experimental conditions, and data collection with computational requirements.

4.1 System Considerations and Simulation Model

A traditional job shop model is used in our simulation study. The model is developed in the SIMAN simulation language (Pegden et al. [23]). A part of the code is written in C language to implement dispatching rules (see Appendix B for a sample model and experimental frame). The simulated shop is comprised of five machines. All other resources (labour, tool, etc.) are assumed to be in ample supply. Job arrivals follow Poisson process and it is assumed that each arrival is of lot size 1. The number of operations of a job is selected from a discrete uniform distribution from 1 to 5. It is assumed that a particular machine cannot be assigned to more than one operation of a job (i.e., non-reentrant job shop). The jobs are randomly routed in the shop. The operation times are generated from an exponential distribution with a mean of 2.5 time units.

Mean utilization (or load) of the shop is set to different levels by adjusting the arrival rate of the jobs. In the uniform job shop case, the mean utilization is set to 65% for low level, and 85% for high level. In the bottleneck case, the utilization of the bottleneck machine is set 75% for low level, and 95% for high level. The other machines have utilizations decreasing with 5% with respect to the bottleneck machine (e.g. 70%, 65%, 60% and 55% for low level).

4.2 Experimental Design

4.2.1 Factors

Four factors are considered in the experiments. These are:

- Flowtime estimation method
- Shop balance
- Shop utilization
- Dispatching rule

Five different flowtime estimation methods are tested in this study:

- Operation-Based Estimation (OBE)
- Total Work Content (TWK)
- Jobs in Queue (JIQ)
- Operation Flowtime Sampling (OFS)
- Congestion and Operation Flowtime Sampling (COFS)

OBE is our proposed estimation method which was already discussed in the previous chapter. OFS and COFS are two methods that showed very good performances in recent studies (Vig and Dooley [32] and [33]). Another method is JIQ that is one of the most popular methods in the literature (Eilon and Chowdhury [10], Ragatz and Mabert [25], Philipoom et al. [24], and etc.) TWK is also a frequently used method in the literature. It is included in this study for the purpose of benchmarking. The mathematical forms of these methods are:

$$\begin{aligned}
\textit{TWK:} \quad & F_i = kP_i \\
\textit{JIQ:} \quad & F_i = k_1P_i + k_2Q_i \\
\textit{OFS:} \quad & F_i = k_1T_i + k_2N_i + k_3P_i \\
\textit{COFS:} \quad & F_i = k_1T_i + k_2Q_i + k_3N_i + k_4P_i
\end{aligned}$$

where,

F_i	=	Flowtime estimate of job i
P_i	=	Total processing time of job i
N_i	=	Number of operations of job i
Q_i	=	Number of jobs in progress along the route of job i.
T_i	=	$A \times N_i$
A	=	$A_1/NR_1 + A_2/NR_2 + A_3/NR_3$
A_1, A_2, A_3	=	Flowtimes of the three most recently completed jobs
NR_1, NR_2, NR_3	=	Number of operations of the three most recently completed jobs

All these methods are tested under two job shop conditions:

- bottleneck shop

- uniform shop

In bottleneck case, the utilizations of the machines are set as explained in the previous section.

Two levels are taken for machine utilizations:

- High utilization (85%)
- Low utilization (65%)

We use three dispatching rules in the experiments:

- FCFS
- MOD
- SPT

FCFS (First Come First Served): Earliest job has the highest priority.

MOD (Modified Operation Due Date): The job with the smallest value of modified operation due date, d'_{ij}, has the highest priority. Modified operation due date of a job is calculated as follows:

$d'_{ij} = max(d_{ij}, t + p_{ij})$

where,

d_{ij} = r_i + (total processing time up to operation j) x k

r_i = release time of job i

k = (d_i - r_i) / total processing time

(assuming that $d_i > r_i$)

d_i = due date of job i

t = current time

p_{ij} = processing time of job i for its jth operation

SPT (Shortest Processing Time): The job with the shortest processing time has the highest priority.

We have chosen these dispatching rules because each represents a different dispatching strategy. MOD assigns priorities that change over time and therefore is one of the *dynamic* rules. Whereas *static* rules assign priorities that do not change over time as long as the job information does not change. SPT is a such rule and hence, it is included in the study (Ragatz and Mabert [25]). FCFS is used as a benchmark rule for comparisons.

4.3 Performance Measures

To evaluate the performances of the flowtime estimation methods, we have used the following criteria:

- Mean Lateness:

  $ML = \sum_{i=1}^{n} L_i/n$

- Standard Deviation of Lateness:

  $STDL = (\sum_{i=1}^{n}(L_i - \bar{L})^2/n)^{1/2}$

- Mean Tardiness:

  $MT = \sum_{i=1}^{n} T_i/n$

- Mean Squared Lateness:

  $MSL = \sum_{i=1}^{n}(Li)^2/n$

- Mean Absolute Lateness:

  $MAL = \sum_{i=1}^{n} |L_i|/n$

- Mean Semi-Quadratic Lateness:

  $MSQL = \sum_{i=1}^{n} V_i/n$
  $V_i = L_i^2$ if $L_i > 0$
  $V_i = |L_i|$ if $L_i \leq 0$

- Mean Flowtime:

  $MF = \sum_{i=1}^{n} F_i/n$

  where,

  F_i : Flowtime estimate of job i
  r_i : Release time of job i
  C_i : Completion time of job i
  Due date of job i : $d_i = r_i + F_i$
  Lateness : $L_i = C_i - d_i$
  Tardiness : $T_i = max(0, C_i - d_i)$
  n : number of jobs completed

One can determine the quality of an estimation method by the accuracy and precision of the estimates it produces. Vig and Dooley [33] define *accuracy* of estimates as the closeness of the individual estimates to their true values; and, *precision* as the variability of the prediction errors. We have selected ML, MAL and MT to measure the accuracy; and, STDL and MSL to measure the variability of the estimates. MSQL is a hybrid performance criterion and can be considered for both accuracy and precision. It penalizes the late jobs severely than the early ones. In general, MT is mostly used when comparing due date assignment methods and it is not a preferred criterion in flowtime estimation. This is because tardiness is calculated only as the positive lateness. Since ML can lead to misleading results when large negative and positive lateness values cross each other, MAL can be considered as a better criterion to measure accuracy. Both STDL and MSL aim to quantify the variability of lateness and there is no significant difference between them when used for the purpose of measuring the precision of the estimates of flowtimes.

In the literature, MF is usually not considered as a performance indicator when comparing the flowtime estimation methods ([32], [33]). It has been observed that when FCFS or SPT is used, the flowtime estimation method and the dispatching rule are completely independent. Therefore, when common random numbers are used, exactly the same performance values are observed for all flowtime estimation methods. It has also been observed that that slightly different MF values are obtained for the MOD case ([32], [33]). Conclusively, we have selected MAL and STDL as our primary criteria for accuracy and precision, respectively. We have to note that although ML, MT and MF are all frequently used in the job shop scheduling literature, they are not much relevant when comparing flowtime estimation methods.

4.4 Sensitivity Conditions

In addition to the standard conditions discussed above, we have also used other test conditions to measure the sensitivity of the flowtime methods to changing shop conditions. These are as follows:

a) Machine Breakdown

b) Processing Time Variation

c) Load Variation in the System

4.4.1 Machine Breakdown

Machine breakdowns are modeled by following the busy time approach proposed by Law and Kelton [19]. The authors recommend that the following gamma distributions can be used for busy time distribution and down time distribution in the absence of data:

Busy Time Distribution:

$$Gamma\left(\alpha_b = 0.7, \beta_b = d_{avg} \times \frac{\epsilon}{0.7(1-\epsilon)}\right)$$

where,

α_b : shape parameter for busy times

β_b : scale parameter for busy times

d_{avg} : mean duration of the down times

ϵ : efficiency level (long-run ratio of the machine busy time to total busy and down times)

Down Time Distribution :

$$Gamma\left(\alpha_d = 1.4, \beta_d = \frac{d_{avg}}{1.4}\right)$$

where,

α_d : shape parameter for down times

β_d : scale parameter for down times

We have selected two levels for mean duration of breakdowns (or, mean downtime), $d_{avg} = 5p_{avg}$ and $d_{avg} = 15p_{avg}$, where p_{avg} is the average operation processing time. Efficiency is our second factor for which we have selected two levels, $\epsilon = 80\%$ and $\epsilon = 90\%$. By changing the mean downtime for each efficiency level, we attempted to model two different cases. In the former case, machines are broken frequently but repaired quickly (i.e., $d_{avg} = 5p_{avg}$) whereas in the later case the frequency of the breakdowns is smaller but the mean downtime is much larger than the former case (i.e., $d_{avg} = 15p_{avg}$).

During simulation experiments, we observed that the system saturates at high utilization rates even for the efficiencies of 96% or above. For that reason, we tested sensitivity of the flowtime methods under low utilization case for all dispatching rules; and, balanced and unbalanced shop conditions.

4.4.2 Processing Time Variation

In practice, processing times are estimated by some mechanisms (e.g., statistical tools, workers, engineers, etc.) and these estimates are used to make various decisions such as due date assignment and scheduling. However, actual processing times can be realized quite differently than the estimated quantities due to variations in machining conditions, material, etc.

In order to model this situation, we perturb the processing times in the experiments. The best estimates are still drawn from the exponential distribution but only some percentages (plus or minus) of the sampled quantities are used for actual processing times.

Processing time variations are incorporated into the simulation model as follows:

$$p'_{ij} = (1 + V \times U[-1, +1]) \times p_{ij}$$

where,

p_{ij} :	processing time value drawn from the exponential distribution function (estimate of the processing time),
V :	level of the processing time variation
$U[-1,+1]$:	uniform distribution with a minimum value -1 and a maximum value +1
p'_{ij}:	processing time deviated from its estimated value (actual value of processing time)

The flowtime methods are tested under three levels of processing time variation, $V = 0.2$, $V = 0.4$ and $V = 0.6$ for balanced and unbalanced shops.

4.4.3 Load Variation

In our study, we also consider load variation in order to model the situation where the system experiences a seasonal demand or some other external factors that cause changes in demand rate over time.

In the model, load variation is achieved by varying the arrival rate of the jobs to the system. This means that the load level of system (consequently, the utilizations of the machines) changes over time. In the pilot experiments, we observed that 500 jobs is quite sufficient to change the load level of the system significantly. Hence, in simulation runs, after the completion of 500 jobs, the arrival rate is updated to a new value as follows:

$$a' = U[a^H_{LV}, a^L_{LV}]$$

where,

LV : load variation level

a' : updated arrival rate

a_{LV}^{H} : arrival rate which makes the load level of the system LV percent higher than the average load level of the system

a_{LV}^{L} : arrival rate which makes the load level of the system LV percent lower than the average load level of the system

Two levels of load variation is used, $LV = 10\%$ and $LV = 20\%$.

4.5 Data Collection and Computational Requirements

The computational study has been implemented in three stages. The first stage is data collection and estimation of the coefficients of the flowtime estimation methods. At the second stage, the performance of the flowtime estimation methods are measured by using the coefficients obtained in the previous stage. Finally, at the last stage, we test sensitivity of the results to machine breakdown, processing time variation and load variation.

4.5.1 First Stage

For each combination of the experimental factors (given in section 4.2), we estimate the coefficients of flowtime estimation methods. For example, twelve sets of coefficients are determined for OBE (3 dispatching rules, 2 levels of system balance, and 2 levels of system utilization).

In general, observations in the data set for estimation of these coefficients are collected by taking long single simulation runs and applying multiple regression to the collected data. This procedure is usually adequate when a dispatching rule does not rely on due date information (e.g., SPT, FCFS).

However, for the rules which utilize due date information, there must also be a mechanism to set due dates which in turns depends on flow allowances. In this case, depending on the initial method of setting flow allowances, one can obtain different coefficient estimates if only one iteration is made. Hence, a single iteration (or replication) will not be sufficient for estimating the coefficients.

Gee and Smith (1993) propose an iterative procedure for this case. The coefficients are estimated at each iteration and used as an input for the next iteration (i.e. the flow allowances are set by these coefficients at the next iteration). The authors have shown that both dramatic improvements in the performance measures and significant changes in the coefficients occur only at the first few iterations. They also reported that complete benefits of iterations are obtained by the fifth or sixth cycle.

In our study, we have also applied this iterative procedure (with six iterations) to obtain reliable coefficient estimates for the due-date dependent rule MOD. A common random number (CRN) variance reduction technique has been also implemented to have the coefficients stabilize within the first few iterations.

Vig and Dooley [32], [33] propose a fourth transformation on the flowtimes to minimize the residuals. We have also applied this transformation to the methods proposed by them (OFS and COFS).

These coefficients of the regression equations have been estimated by 160 simulation runs (60 runs for the first iteration of all dispatching rules, and 100 runs for the remaining iterations of the MOD dispatching rule). At each simulation run we have collected $5,000$ observations for each regression equation. In order to apply multiple regression analysis, observations in the data set should be independent. But in a typical simulation run from a queueing system, consecutive observations are usually positively correlated. In order to overcome this difficulty, a random sample approach with a certain lag is proposed (Ragatz and Mabert [25], Vig and Dooley [32], Kaplan and Unal [18]). According to this approach, a sample is collected from the nonconsequent observations in a given simulation run. In the preliminary runs we observed that skipping 50 jobs and taking one observation attains the independence condition. Hence, the 5,000 observations have been collected by a simulation run of 25,000 job completions which approximately took 3 hours of run time on SUN SPARC STATION 2/50 workstations.

The coefficients of all the regression equations of the flowtime estimation methods are given from Table A.1 to Table A.44 in Appendix A. The R^2 values for each regression equation and the p-values of the coefficients are also presented in these tables. R^2 is the coefficient of determination and quantifies the proportion of the variation of flowtimes explained by the regression model (i.e., the flowtime estimation method). Higher R^2 values in Tables A.1 - A.44 mean that the data used in the regression analysis are better explained by the estimated model. p-value of a coefficient is 1 minus the probability that the coefficient is significantly different than zero. So, if a p-value of a coefficient gets nearer to zero, we are more confident that the respective variable significantly affects the dependent variable of the model (i.e. flowtimes in our case).

During the first stage, we also made the following observations:

- For all flowtime estimation methods, the R^2 values are quite high for the FCFS rule. However, the R^2 values for SPT and MOD are rather smaller as compared to FCFS. Thus, one may infer that the regression equations estimated for FCFS explain a larger proportion of variation of the flowtimes than the regression equations estimated for SPT and MOD.

  This observation can be attributed to the fact that SPT and MOD rules create a more dynamic environment such that the shop conditions change rather quickly with respect to the FCFS rule; dispatching in the shop is more frequently changed due to the changes in the ranking of jobs in the queues, which is a quite difficult task to forecast when compared with FCFS.

- After a few iterations of the iterative procedure, the coefficients are stabilized for almost all flowtime estimation methods. But some exceptions have also been noted for TWK and JIQ (Tables A.41- A.44). This may be due to the fact that these methods are based on fewer factors.

- For the proposed estimation method (OBE), the R^2 values of equations for the earlier operations in the process route (1st or 2nd operations of a job) are quite high with respect to the R^2 values of the equations of the later operations, when the dispatching rule is FCFS. But the same observation is not made for the MOD and SPT rules. On the contrary, it has been also noted that the equations for the former operations sometimes can take smaller R^2 values for MOD and SPT (Tables A.5- A.10). This is probably due to the same line of reasoning that we made for the first observation above.

  Even though the FCFS rule produces lower values of R^2 for the later operations, their overall values are higher than the ones obtained for SPT and MOD.

- It is seen that R^2 values for the OFS and COFS rules are quite high when compared to other methods. This is due to the fourth transformation applied on the flowtimes while estimating the coefficients for these methods. Weisberg [35] proposes that if the order of transformation is higher than 3, the models fit very good to the data but serious numerical problems may arise. Neter, Wasserman and Kutner [22] also claim that when the order is high, one can get better fits, but poor interpolation and extrapolation results may be obtained. Hence, we can say that the R^2 values obtained for these rules are not performance indicators of OFS and COFS.

- Number of operations of job i (N_i) used in the COFS and OFS methods sometimes appears to be an insignificant factor in the flowtime estimation. For example, when the shop is balanced at low utilization level, the p-value of N_i is observed as 0.9194 ($0.9194 > 0.05$) for SPT (Table A.36). This means that it has almost no effect on the flowtime of a job in the existence of other variables.

4.5.2 Second Stage

In the second stage, by using the coefficients estimated in the previous stage, we take simulation runs (using the method of batch means) for each design point (60 design point in total) to obtain the performances of the flowtime estimation methods under various operating conditions. Specifically, we take 40 batches of simulation runs, each of which consists of 2500 job completions. Thus, each simulation run consists of 100, 000 jobs in total.

4.5.3 Third stage

As often experienced in practice, the system conditions may continuously change over time. The settings of the system when the model has been first constructed could become quite different in the future. These type of variations may come from the change in the arrival process, unexpected events in the shop and other factors that have not been accounted for when the model was first designed. One can argue that the models developed so far becomes obsolete in such cases. But, since the re-construction of models are not always so easy and economical in real life, the same models can be used to some extent unless they have unacceptable impacts on the system performances.

In the third stage, we model and test the sensitivity of the results to these three main factors: machine breakdown, processing time variation and load variation. In these cases, new coefficients for the flowtime estimation methods are not generated. But instead, the previously obtained coefficients are used to estimate the flowtimes in the simulation experiments.

Again, we take 40 batches each consisting of 2500 job completions. Thus, each simulation run includes 100, 000 jobs in total. We replicate these runs for all the conditions specified in the previous section 4.4; that is, 120 simulations runs for machine breakdown, 120 runs for processing time variation and 60 runs for load variation, resulting to 300 simulation runs in total for the third stage.

Chapter 5

Computational Results

5.1 Introduction

In this chapter, we present and discuss the results of the flowtime estimation methods for the performance criteria specified in section 4.3. These are: Mean Lateness (ML), Standard Deviation of Lateness (STDL), Mean Tardiness (MT), Mean Squared Lateness (MSL), Mean Absolute Lateness (MAL) and Mean Semi-Quadratic Lateness (MSQL). Mean Flowtime (MF) results will also be presented; however, these results will not be taken into account when discussing the performance of the flowtime estimation methods. Although MF can be considered as a performance indicator when comparing dispatching rules or other different shop configurations, it is not a performance criterion for comparing flowtime estimation methods. This is because that the same MF values are obtained for each estimation method due to the use of common random numbers in the experiments. As explained in section 4.3, our primary criteria are MAL and STDL for accuracy and precision of the flowtime estimates, respectively.

This chapter is composed of mainly two parts. In the first part, we discuss the results of the second stage of the experiments. In the second part, we evaluate the sensitivity results of the flowtime estimation methods to different experimental conditions, which have been tested in the third stage of our experiments.

5.2 Second Stage Results

In the second stage, by using the coefficients estimated in the first stage of our experiments, the flowtime estimation methods have been tested under various shop conditions.

In this section, we discuss the results for each performance criteria separately. Moreover, we also implement analysis of variance (ANOVA) on the performance results to measure the significance of the main factors and their interactions. The results of the simulation experiments are summarized in Tables 5.1 - 5.4.

5.2.1 Mean Absolute Lateness

The results of MAL are presented in four tables. Table 5.1 and 5.2 show performance of the flowtimes estimation methods at low utilization level for both the balanced and unbalanced shop cases. Tables 5.3 and 5.4 give the results of the high utilization cases.

In general, OBE outperforms other flowtime estimation methods for the MAL criterion as also indicated by the boldface numbers in tables. In order to test the statistical significance of the proposed method, we have also conducted paired t-tests which compare OBE with the next best method at a significance level of 5%. As shown by "$\star$" (indicating that the difference is significant), OBE is better than the other competitive methods for the MAL criterion.

Table 5.1: Performance Results for Balanced Shop
Under Low Utilization (65%) Level

Performance Measure	Dispatching Rule	OBE	TWK	JIQ	COFS	OFS
Mean Lateness	FCFS	0.60	3.07	0.96	−1.11	**−0.43***
	MOD	0.64	0.71	**−0.02***	−0.94	−1.17
	SPT	0.97	0.36	**−0.22***	−1.40	−1.35
Std. Dev. of Lateness	FCFS	**6.56***	12.35	7.86	15.72	14.74
	MOD	**5.99***	8.00	6.59	11.59	11.90
	SPT	**7.62***	8.70	8.21	15.22	15.18
Mean Tardiness	FCFS	**2.48***	6.07	3.19	4.60	4.84
	MOD	2.15	2.77	**1.97***	2.95	2.91
	SPT	2.75	2.86	**2.40***	3.70	3.72
Mean Squared Lateness	FCFS	**43.61***	164.67	62.94	251.44	218.72
	MOD	**36.67***	65.22	43.81	135.93	143.82
	SPT	**59.68***	76.70	68.32	235.42	233.99
Mean Absolute Lateness	FCFS	**4.37***	9.07	5.42	10.32	10.12
	MOD	**3.67***	4.82	3.96	6.87	6.98
	SPT	**4.54***	5.36	5.02	8.80	8.79
Mean Semi-Quadratic Lateness	FCFS	**29.38***	132.15	44.93	74.00	82.96
	MOD	**29.63***	51.09	33.68	40.86	40.44
	SPT	**49.99***	58.37	52.34	68.25	69.10
Mean Flowtime	FCFS	19.44	19.44	19.44	19.44	19.44
	MOD	14.78	**14.57**	14.90	15.37	15.32
	SPT	14.28	14.28	14.28	14.28	14.28

$\star$: Statistically significant at 5%

Table 5.2: Performance Results for Unbalanced Shop
Under Low Utilization (65%) Level

Performance Measure	Dispatching Rule	OBE	TWK	JIQ	COFS	OFS
Mean Lateness	FCFS	0.86	3.45	0.92	−1.34	**−0.28***
	MOD	0.82	**−0.06***	−0.28	−1.28	−1.04
	SPT	1.19	0.54	**−0.13***	−0.73	−0.70
Std. Dev. of Lateness	FCFS	**6.81***	14.71	8.54	17.96	16.40
	MOD	**7.36***	10.08	8.71	13.17	13.05
	SPT	**9.64***	11.11	10.74	16.78	16.80
Mean Tardiness	FCFS	**2.69***	7.03	3.38	5.03	5.43
	MOD	2.42	2.64	**2.07***	3.01	3.12
	SPT	3.09	3.18	**2.71***	4.21	4.22
Mean Squared Lateness	FCFS	**47.35***	234.18	74.14	330.73	271.02
	MOD	**56.25***	105.27	78.76	176.04	172.63
	SPT	**96.61***	127.75	119.20	286.21	286.62
Mean Absolute Lateness	FCFS	**4.52***	10.61	5.84	11.40	11.15
	MOD	**4.02***	5.34	4.41	7.29	7.28
	SPT	**4.99***	5.81	5.54	9.14	9.15
Mean Semi-Quadratic Lateness	FCFS	**32.91***	188.75	51.94	91.22	109.73
	MOD	**47.31***	82.81	65.11	53.14	62.43
	SPT	**83.78***	107.52	100.75	114.63	115.93
Mean Flowtime	FCFS	21.37	21.37	21.37	21.37	21.37
	MOD	15.55	**15.30**	15.67	16.23	16.15
	SPT	14.87	14.87	14.87	14.87	14.87

$\star$: Statistically significant at 5%

Table 5.3: Performance Results for Balanced Shop
Under High Utilization (85%) Level

Performance Measure	Dispatching Rule	OBE	TWK	JIQ	COFS	OFS
Mean Lateness	FCFS	**0.42**	9.24	1.26	−0.62	1.31
	MOD	0.72	−1.02	−1.92	−0.19	**−0.17**
	SPT	−1.21	−1.04	−1.90	**0.27***	0.39
Std. Dev. of Lateness	FCFS	**11.36***	29.89	13.87	24.83	24.07
	MOD	**12.17***	19.71	16.38	18.51	20.00
	SPT	**22.50***	25.51	25.46	30.86	30.94
Mean Tardiness	FCFS	**4.03***	16.42	5.54	8.49	9.53
	MOD	**2.17***	3.60	2.47	4.03	4.26
	SPT	**4.46***	5.01	4.71	7.31	7.38
Mean Squared Lateness	FCFS	**130.94***	1028.64	195.96	634.70	589.08
	MOD	**159.34***	420.18	290.33	354.03	414.92
	SPT	**535.65***	691.62	691.14	987.48	991.32
Mean Absolute Lateness	FCFS	**7.64***	23.60	9.82	17.60	17.76
	MOD	**5.03***	8.21	6.86	8.26	8.68
	SPT	**10.14***	11.05	11.33	14.36	14.37
Mean Semi-Quadratic Lateness	FCFS	**75.66***	798.74	126.91	246.26	317.60
	MOD	**140.02***	350.93	246.09	219.65	246.33
	SPT	**411.60***	598.06	600.97	617.15	626.81
Mean Flowtime	FCFS	45.30	45.30	45.30	45.30	45.30
	MOD	26.58	**24.74**	26.61	26.40	26.23
	SPT	22.27	22.27	22.27	22.27	22.27

$\star$: Statistically significant at 5%

Table 5.4: Performance Results for Unbalanced Shop
Under High Utilization (85%) Level

Performance Measure	Dispatching Rule	OBE	TWK	JIQ	COFS	OFS
Mean Lateness	FCFS	**0.39***	15.59	1.34	−2.61	3.68
	MOD	−2.46	−0.70	−2.77	**0.30**	1.26
	SPT	−2.26	**−1.85***	−4.02	2.02	2.15
Std. Dev. of Lateness	FCFS	**12.59***	43.84	16.27	36.37	35.61
	MOD	**27.94***	47.59	42.49	40.34	43.51
	SPT	**49.05***	58.56	64.59	62.15	62.28
Mean Tardiness	FCFS	**4.45***	25.85	6.42	11.28	15.08
	MOD	**3.04***	5.57	4.15	5.61	6.33
	SPT	**6.55***	7.32	10.25	10.35	10.42
Mean Squared Lateness	FCFS	**165.19***	2587.75	274.82	1567.49	1409.42
	MOD	**1132.58***	3312.89	2659.13	2247.65	2598.84
	SPT	**3139.04***	4691.55	5414.94	5014.48	5030.09
Mean Absolute Lateness	FCFS	**8.51***	36.11	11.50	25.18	26.47
	MOD	**8.54***	11.85	11.08	10.93	11.41
	SPT	**15.36***	16.48	24.52	18.69	18.69
Mean Semi-Quadratic Lateness	FCFS	**94.07***	2130.42	174.83	468.89	900.17
	MOD	**1025.48***	3198.49	2556.11	2005.43	2356.47
	SPT	**2625.94***	4505.78	4880.54	4413.72	4434.25
Mean Flowtime	FCFS	63.09	63.09	63.09	63.09	63.09
	MOD	33.41	**30.20**	33.15	32.46	31.59
	SPT	26.07	26.07	26.07	26.07	26.07

$\star$: Statistically significant at 5%

As the second best method, JIQ exhibits the next closest performance to OBE. However, when the utilization of the shop is high and the dispatching rule is SPT, TWK gives the second best results. These findings support that processing time information is more valuable than route congestion information when the shop is highly loaded and the dispatching is conducted with the SPT rule.

Moreover, it is observed that MOD dispatching rule produces the lowest MAL values in most of the shop conditions for all the flowtime estimation methods. This is a kind of expected result because MOD is the only due date based rule which utilizes the flow allowance information.

It is interesting to note that the worst MAL performance is exhibited for SPT when OBE is implemented as the flowtime estimation method. It is also observed that SPT mostly gives the second best performance values when other methods are implemented. Thus, one should be careful when using OBE if the dispatching is conducted by SPT in the system. Moreover, the same discussion is also valid for the other methods. For these methods, the worst MAL performance is obtained when the FCFS rule is used. But FCFS produces the second best results when OBE is used in the flowtime estimation process.

The results also show that the performance of the flowtime estimation methods deteriorates as the utilization of the shop increases or when the shop is not balanced. In both cases, differences in the relative performances of the flowtime estimation methods increase significantly (see Figures 5.1 - 5.6).

Table 5.5: Analysis of Variance for Mean Absolute Lateness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	103532.844689	167.94	0.0001	yes
Error	2301	14475.054701			
A	39	4508.8870716	18.38	0.0001	yes
F	4	13507.6697131	536.81	0.0001	yes
D	2	15137.8065276	1203.18	0.0001	yes
B	1	5265.7548754	837.06	0.0001	yes
U	1	33835.4790550	5378.59	0.0001	yes
F*D	8	11588.6314787	230.27	0.0001	yes
F*B	4	338.5049736	13.45	0.0001	yes
F*U	4	2409.7964481	95.77	0.0001	yes
D*B	2	361.4696643	28.73	0.0001	yes
D*U	2	4748.8748836	377.45	0.0001	yes
B*U	1	3466.1594554	550.99	0.0001	yes
F*D*B	8	1468.6904112	29.18	0.0001	yes
F*D*U	8	5284.0927552	105.00	0.0001	yes
F*B*U	4	229.8215686	9.13	0.0001	yes
D*B*U	2	277.2954482	22.04	0.0001	yes
F*D*B*U	8	1103.9103597	21.94	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table 5.6: Analysis of Variance for Mean Absolute Lateness Under Low Utilization (65%) Level

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	6993.10652167	778.43	0.0001	yes
Error	1131	149.41877625			
A	39	191.99764125	37.26	0.0001	yes
F	4	4386.02571333	8299.82	0.0001	yes
D	2	1595.15736067	6037.14	0.0001	yes
B	1	93.72753075	709.45	0.0001	yes
F*D	8	688.17965017	651.13	0.0001	yes
F*B	4	8.74655133	16.55	0.0001	yes
D*B	2	12.37455800	46.83	0.0001	yes
F*D*B	8	16.89751617	15.99	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance

Table 5.7: Analysis of Variance for Mean Absolute Lateness Under High Utilization (85%) Level

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	65706.8510657	96.52	0.0001	yes
Error	1131	11323.0439713			
A	39	7319.4813837	18.75	0.0001	yes
F	4	11531.4404478	287.95	0.0001	yes
D	2	18291.5240505	913.52	0.0001	yes
B	1	8638.1868000	862.82	0.0001	yes
F*D	8	16184.5445837	202.07	0.0001	yes
F*B	4	559.5799908	13.97	0.0001	yes
D*B	2	626.3905545	31.28	0.0001	yes
F*D*B	8	2555.7032547	31.91	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance

Table 5.8: Analysis of Variance for Mean Absolute Lateness for Balanced Shop

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	25552.2356557	525.94	0.0001	yes
Error	1131	808.0671230			
A	39	658.76653200	23.64	0.0001	yes
F	4	5703.23482117	1995.61	0.0001	yes
D	2	5531.23631667	3870.86	0.0001	yes
U	1	7821.26868033	10946.93	0.0001	yes
F*D	8	2767.53982333	484.19	0.0001	yes
F*U	4	659.77963717	230.86	0.0001	yes
D*U	2	1453.41348467	1017.13	0.0001	yes
F*D*U	8	956.99636033	167.43	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, U: Utilization

Table 5.9: Analysis of Variance for Mean Absolute Lateness for Unbalanced Shop

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	74728.6636110	106.66	0.0001	yes
Error	1131	11653.1781249			
A	39	5863.9299926	14.59	0.0001	yes
F	4	8142.9398655	197.58	0.0001	yes
D	2	9968.0398752	483.72	0.0001	yes
U	1	29480.3698301	2861.22	0.0001	yes
F*D	8	10289.7820665	124.83	0.0001	yes
F*U	4	1979.8383795	48.04	0.0001	yes
D*U	2	3572.7568472	173.38	0.0001	yes
F*D*U	8	5431.0067545	65.89	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, U: Utilization

Another important finding is that COFS and OFS methods perform almost the same for all shop conditions. Their performance, in general, are the worst of all, except for the unbalanced and highly utilized shop cases. It seems that they cannot even compete with TWK. In a way, these results support our proposition made in the previous chapter about the high R^2 values for COFS and OFS (see Section 4.5.1).

We have also applied Analysis of Variance (ANOVA) on the simulation results. The ANOVA table for MAL is given in Table 5.5. We observed that all the main factors (flowtime estimation method (F), dispatching rule (D), shop balance (B) and utilization level (U)) are significant at 5% significance level. Moreover, we note that the blocking factor is also significant. This means that common random number (CRN) variance reduction technique used in the experiments, was very effective in reducing the noise in the data. All two and higher way interactions of the main factors are also found to be significant. In order to see the relative effects of the factors with respect to each shop condition, we have also repeated ANOVA for different shop conditions by fixing either the balance or the utilization level of the system. The purpose was to see whether the factors are still significant when the shop conditions are fixed to certain levels (i.e., high utilization, low utilization, balanced and unbalanced). As shown in Tables 5.6 - 5.9, the main factors and their interactions are still significant in these cases.

The interactions of the flowtime estimation methods with the shop utilization levels are displayed in Figures 5.1 - 5.3 for each dispatching rule. In general, we observed that increasing the utilization level of the system increases significantly the MAL performance values of the flowtime estimation methods for all of the dispatching rules. However, it is also noted that some of the methods are more sensitive to the utilization level when compared with others. For example, the performance of TWK deteriorates much more, when the dispatching rule is FCFS and MOD. In the SPT case, however, the performance of JIQ is affected more than any other flowtime estimation methods.

We also note that OBE is quite robust to the increase in the load level (i.e. it is the method which is affected the least from the changes in the load level of the system). Among the other methods tested, the following flowtime estimation methods showed the second robust performance: JIQ for FCFS, COFS and OFS for MOD, and TWK for SPT.

The interactions of the flowtime estimation methods with the shop balance are also depicted in Figures 5.4 - 5.6. It is observed that deterioration of the shop balance negatively influences the MAL criterion. This influence is rather modest when the shop is lightly loaded. However, the effect is magnified in the highly utilized shop case. It is interesting to note that JIQ performance is affected much more than any other methods for the SPT rule in the high utilization case. From the above observations made for JIQ, we can conclude that JIQ reacts more nervously to the changes of the shop balance and system load when the dispatching rule is SPT.

Figure 5.1: Mean Absolute Lateness (MAL) versus Utilization for FCFS

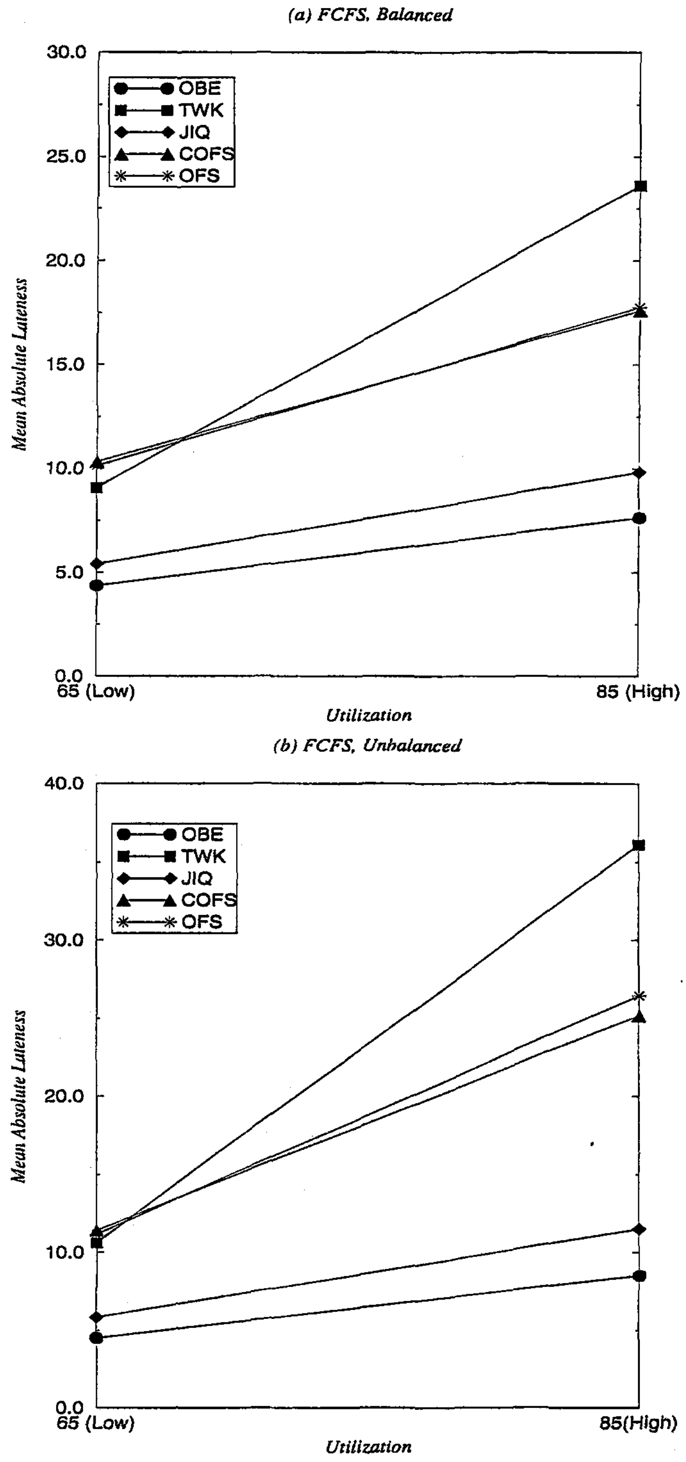


Figure 5.2: Mean Absolute Lateness (MAL) versus Utilization for MOD

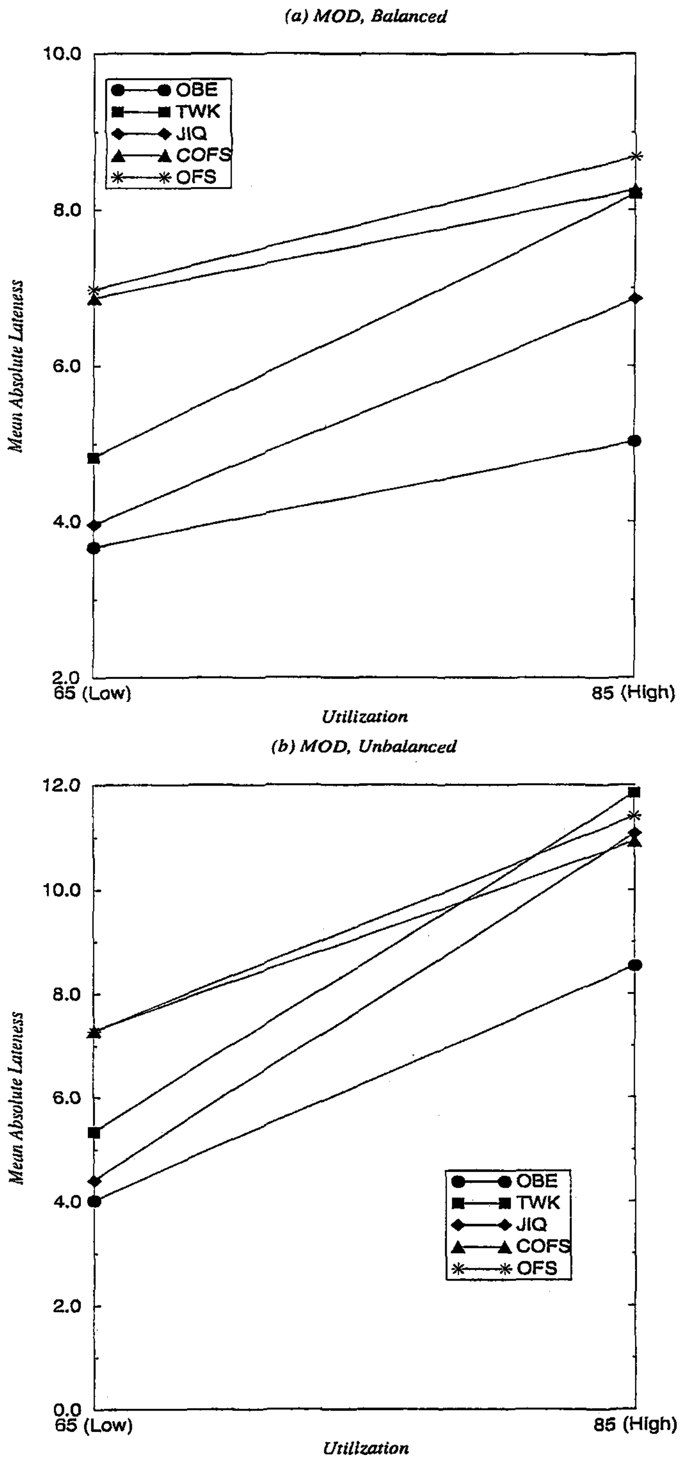


Figure 5.3: Mean Absolute Lateness (MAL) versus Utilization for SPT

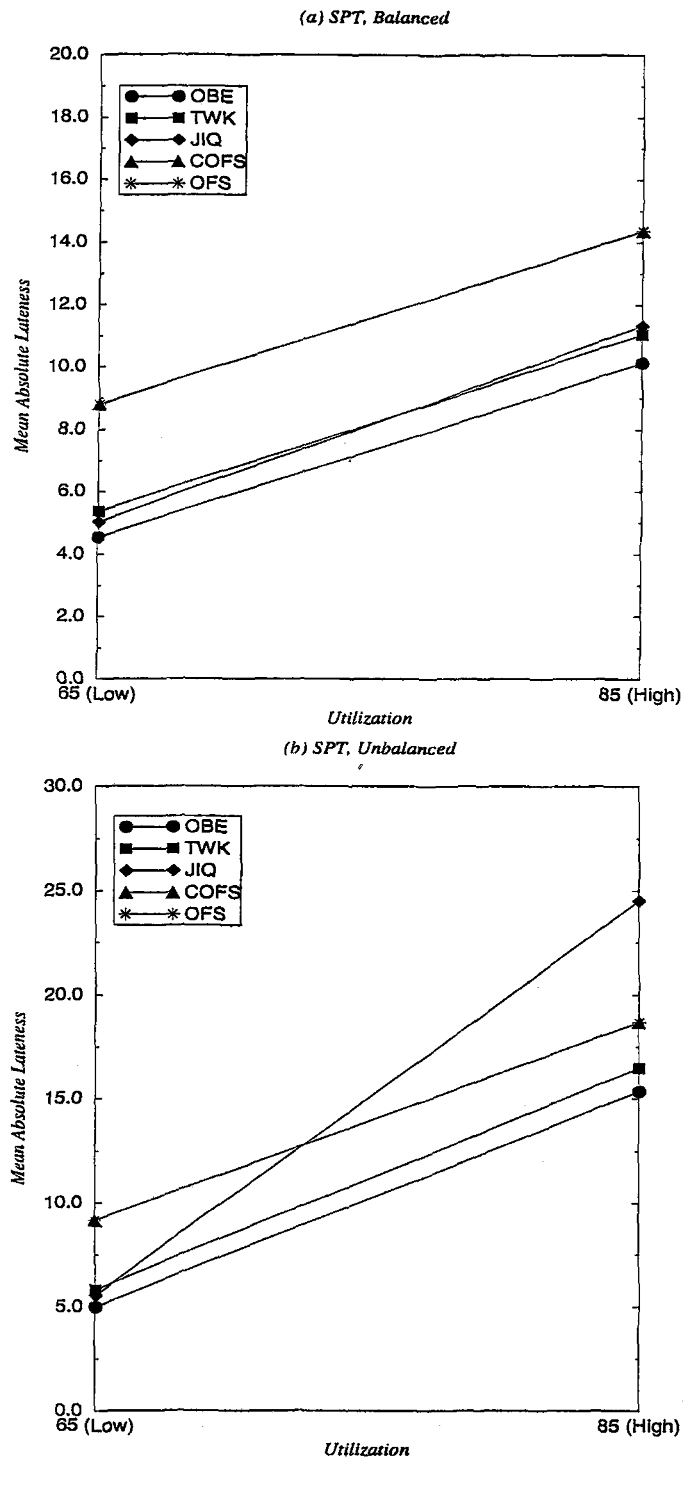


Figure 5.4: Mean Absolute Lateness (MAL) versus Balance for FCFS

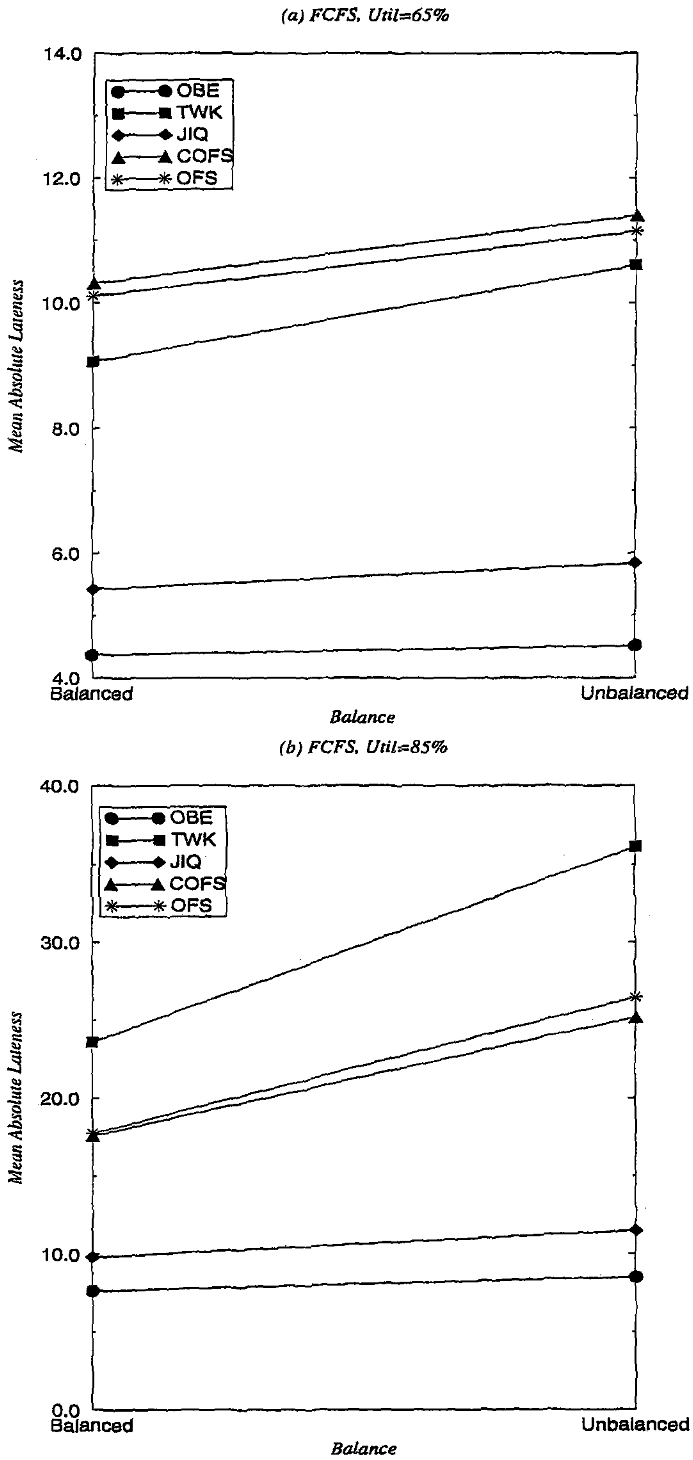
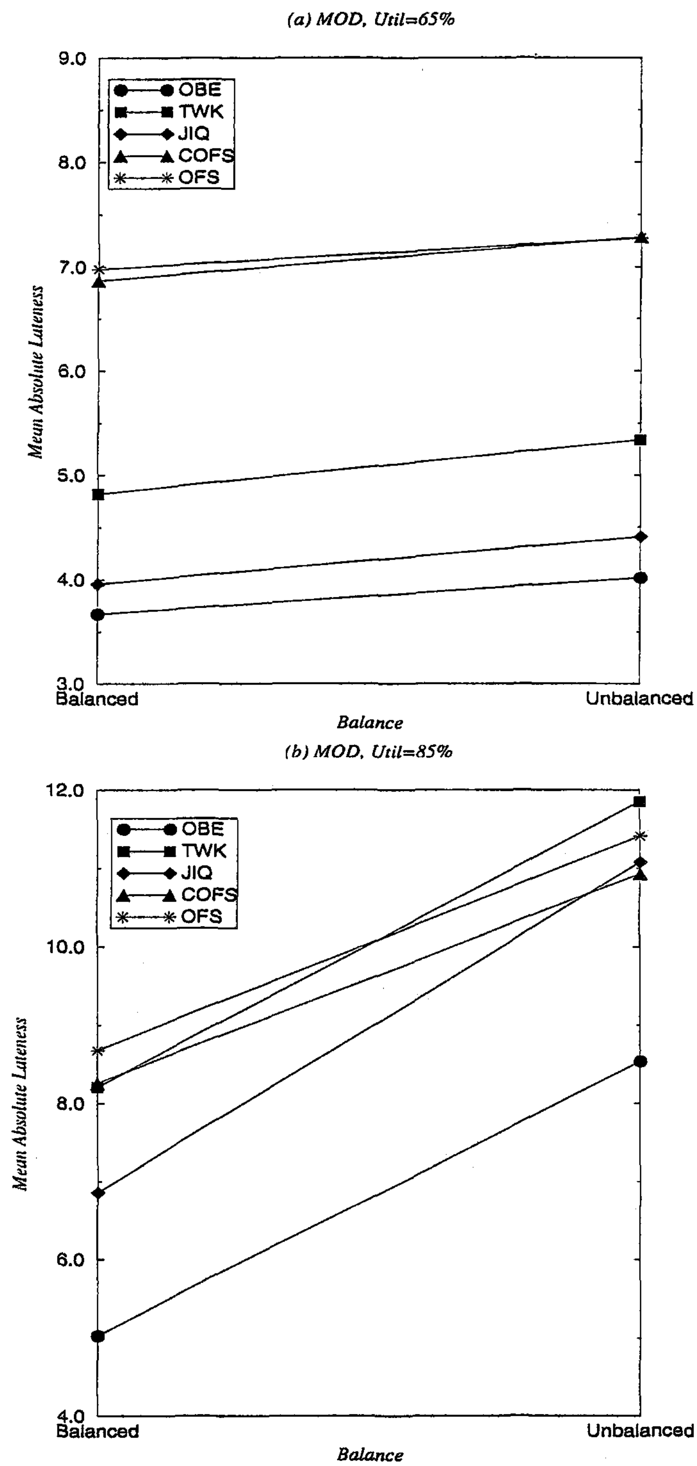


Figure 5.5: Mean Absolute Lateness (MAL) versus Balance for MOD



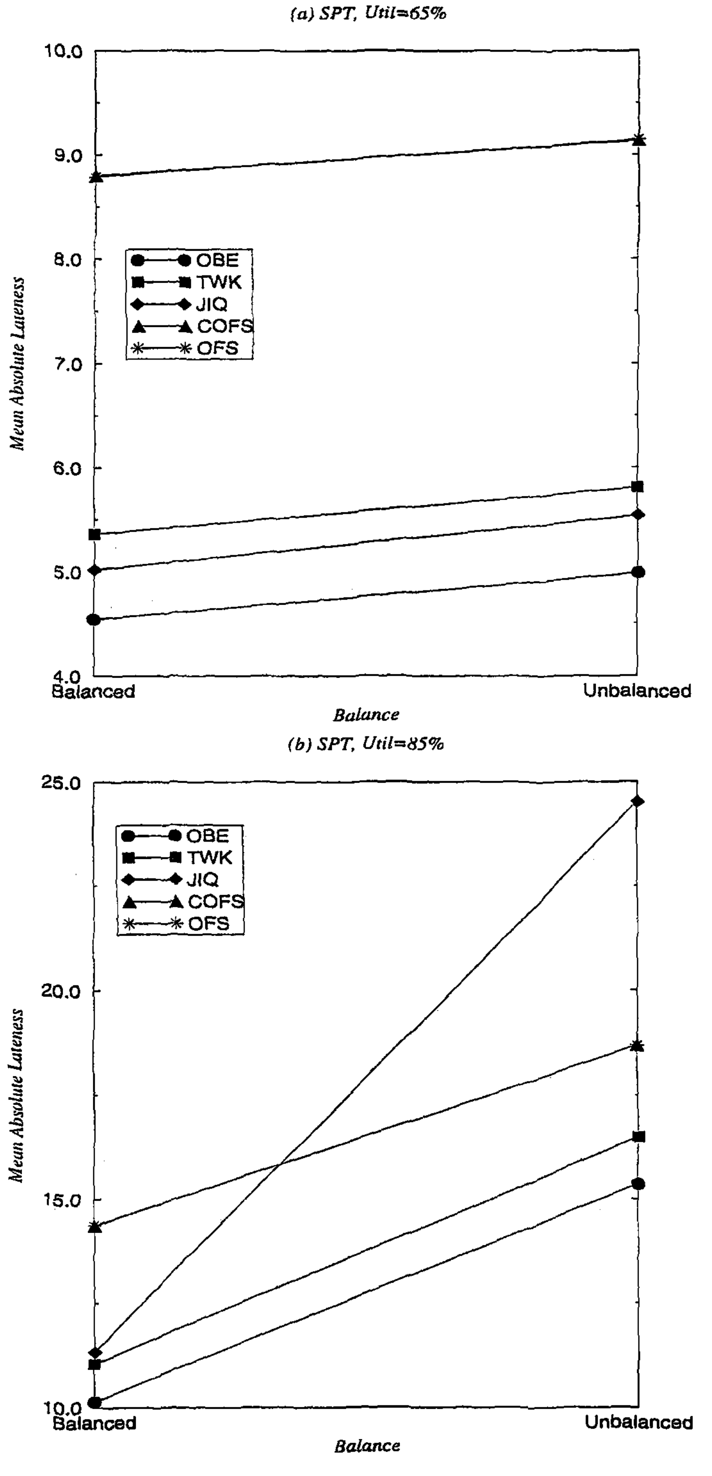
In order to test the differences of the flowtime estimation methods, we have applied Duncan's Multiple Range test for the main effects of the factors. The results are given in Table 5.10. In this table, N gives the number of observations used when applying the test. The methods are grouped by levels and each level is represented by a letter. The levels which are statistically different from each other at a significance level of 5% are labeled with different letters. The methods are also ranked from the worst method to the best method. The results indicate that OBE is the best and JIQ is the next best flowtime estimation method for the MAL measure. Moreover, OBE is always at a separate level (i.e. indicated by a different letter than the other methods) by only itself. This means that it is always significantly better than the other methods for all utilization and shop balance levels. According to Duncan's grouping, when all the factors are included, OFS, COFS and TWK are grouped to the same level indicating no statistical difference between them. However, the ranks of these methods are changed when the shop conditions (balance or utilization) are set to different levels (see Table 5.10).

5.2.2 Standard Deviation of Lateness

The results for STDL are given in Tables 5.1 - 5.4. It is observed again that OBE is the best method among all the flowtimes estimation methods. Paired t-test results also confirm this statement. As it was noted for the MAL criterion, JIQ appears to be the second best method except for the case in which the shop is highly utilized and the dispatching rule is SPT. We also observe that COFS and OFS display the worst performances among all the methods. However, COFS become the third best method for MOD rule when the shop is highly utilized.

Another observation is that that FCFS gives the best STDL values whereas SPT yields the worst. This is due to the dynamic nature of the SPT rule which increases the variability in the system. As it was also observed by Schultz [27], SPT causes quite longer waiting times for some jobs when compared to the FCFS rule.

Figure 5.6: Mean Absolute Lateness (MAL) versus Balance for SPT



We also note that deteriorating the shop balance, or increasing utilization of the shop. negatively affects the STDL performance. As it was noted for MAL. differences in the relative performances of the flowtime estimation methods become more significant in both of these cases.

The ANOVA results for STDL are given in Table 5.11. The results indicated that all the main factors and the blocking factor are significant. Most of the two way and three way interactions are also significant except the three way interaction of F (flowtime estimation method), D (dispatching method). and B (shop balance) factors.

In order to see the relative effects of the factors with respect to each shop condition, we have also repeated ANOVA for different shop conditions by fixing either the balance or the utilization level of the system. The results indicated that the main factors and their interactions are still significant (Tables 5.12 - 5.15).

In Figures 5.7 - 5.9, we illustrate the interactions of the flowtime estimation methods with the utilization of the shop. It is clear that utilization of the shop affects significantly the STDL performance of the flowtime estimation methods. Moreover, we observe that TWK is affected the most from the load level changes when the dispatching rule is FCFS and MOD (see the lines of TWK which are more steeper in figures as compared to other methods). When the dispatching rule is SPT and the shop is not balanced, JIQ performance is worsened more than the other methods as the load level increases.

Table 5.10: Duncan's Multiple Range Tests for MAL

Levels	Mean	N	Method
All Factors Included			
A	12.5706	480	OFS
A	12.3921	480	COFS
A	12.3598	180	TWK
B	8.7746	480	JIQ
C	6.7764	480	**OBE**
Utilization=65%			
A	8.96967	240	COFS
A	8.90987	240	OFS
B	6.83592	240	TWK
C	5.03192	240	JIQ
D	4.35242	240	**OBE**
Utilization=85%			
A	17.8838	240	TWK
B	16.2313	240	OFS
B	15.8146	240	COFS
C	12.5173	240	JIQ
D	9.2003	240	**OBE**
Balanced Shop			
A	11.11608	240	OFS
A	11.03367	240	COFS
B	10.35300	240	TWK
C	7.06763	240	JIQ
D	5.89696	240	**OBE**
Unbalanced Shop			
A	14.3667	240	TWK
B A	14.0250	240	OFS
B	13.7506	240	COFS
C	10.4816	240	JIQ
D	7.6557	240	**OBE**

Table 5.11: Analysis of Variance for Standard Deviation of Lateness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	667631.357780	50.59	0.0001	yes
Error	2301	309827.658010			
A	39	86632.500732	16.50	0.0001	yes
F	4	41043.803271	76.21	0.0001	yes
D	2	40280.073090	149.57	0.0001	yes
B	1	79176.330130	588.02	0.0001	yes
U	1	267204.708797	1984.45	0.0001	yes
F*D	8	12194.895406	11.32	0.0001	yes
F*B	4	2217.584826	4.12	0.0025	yes
F*U	4	7896.206921	14.66	0.0001	yes
D*B	2	15610.863893	57.97	0.0001	yes
D*U	2	35011.285724	130.01	0.0001	yes
B*U	1	57411.829662	426.38	0.0001	yes
F*D*B	8	1518.875345	1.41	0.1870	no
F*D*U	8	4719.294630	4.38	0.0001	yes
F*B*U	4	1574.983285	2.92	0.0200	yes
D*B*U	2	14211.381096	52.77	0.0001	yes
F*D*B*U	8	926.740971	0.86	0.5495	no

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table 5.12: Analysis of Variance for Standard Deviation of Lateness Under Low Utilization (65%) Level

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	16791.4038140	289.89	0.0001	yes
Error	1131	963.4119297			
A	39	1100.9468303	33.14	0.0001	yes
F	4	11956.0861895	3508.97	0.0001	yes
D	2	1592.8838052	934.99	0.0001	yes
B	1	872.5849653	1024.37	0.0001	yes
F*D	8	1150.0465340	168.76	0.0001	yes
F*B	4	38.8912588	11.41	0.0001	yes
D*B	2	17.8842622	10.50	0.0001	yes
F*D*B	8	62.0799687	9.11	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance

Table 5.13: Analysis of Variance for Standard Deviation of Lateness Under High Utilization (85%) Level

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	462368.059601	33.42	0.0001	yes
Error	1131	230131.431649			
A	39	164264.368333	20.70	0.0001	yes
F	4	36983.924003	45.44	0.0001	yes
D	2	73698.475009	181.10	0.0001	yes
B	1	135715.574827	666.99	0.0001	yes
F*D	8	15764.143502	9.68	0.0001	yes
F*B	4	3753.676853	4.61	0.0011	yes
D*B	2	29804.360726	73.24	0.0001	yes
F*D*B	8	2383.536348	1.46	0.1658	no

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance

Table 5.14: Analysis of Variance for Standard Deviation of Lateness for Balanced Shop

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	74668.0680193	195.53	0.0001	yes
Error	1131	6351.5771953			
A	39	5706.6405547	26.06	0.0001	yes
F	4	14192.4172638	631.80	0.0001	yes
D	2	7051.1915182	627.79	0.0001	yes
U	1	38450.6444083	6846.75	0.0001	yes
F*D	8	3401.9631102	75.72	0.0001	yes
F*U	4	1460.7127292	65.03	0.0001	yes
D*U	2	3411.1346532	303.70	0.0001	yes
F*D*U	8	993.3637818	22.11	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, U: Utilization

Table 5.15: Analysis of Variance for Standard Deviation of Lateness for Unbalanced Shop

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	68	576654.031849	39.86	0.0001	yes
Error	1131	240609.008597			
A	39	143792.932396	17.33	0.0001	yes
F	4	29068.970834	34.16	0.0001	yes
D	2	48839.745465	114.79	0.0001	yes
U	1	286165.894051	1345.14	0.0001	yes
F*D	8	10311.807641	6.06	0.0001	yes
F*U	4	8010.477477	9.41	0.0001	yes
D*U	2	45811.532166	107.67	0.0001	yes
F*D*U	8	4652.671820	2.73	0.0055	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, U: Utilization

The interactions of flowtime estimation methods with the shop balance are also depicted in Figures 5.10 - 5.12. These figures suggest that shop balance affects considerably the STDL performance of the methods. For the FCFS case, we see that the impact of the shop balance is minimum for OBE and JIQ. For the other dispatching rules, it is observed that impact of the balance information on the flowtimes estimation method is nearly the same. However, an exception is also noted for JIQ when the shop is highly utilized and the dispatching rule is SPT.

Duncan's multiple range tests have also been implemented to rank the flowtime estimation methods (Table 5.16). The results indicated that OBE is again the best method and JIQ is the second best. This is followed by TWK, COFS and OFS. In general, COFS and OFS are the worst methods. But TWK displays the worst performance for highly loaded and unbalanced shop cases. In general, OFS and COFS methods appeared to be the worst methods in the other conditions.

Figure 5.7: Standard Deviation of Lateness (STDL) versus Utilization for FCFS

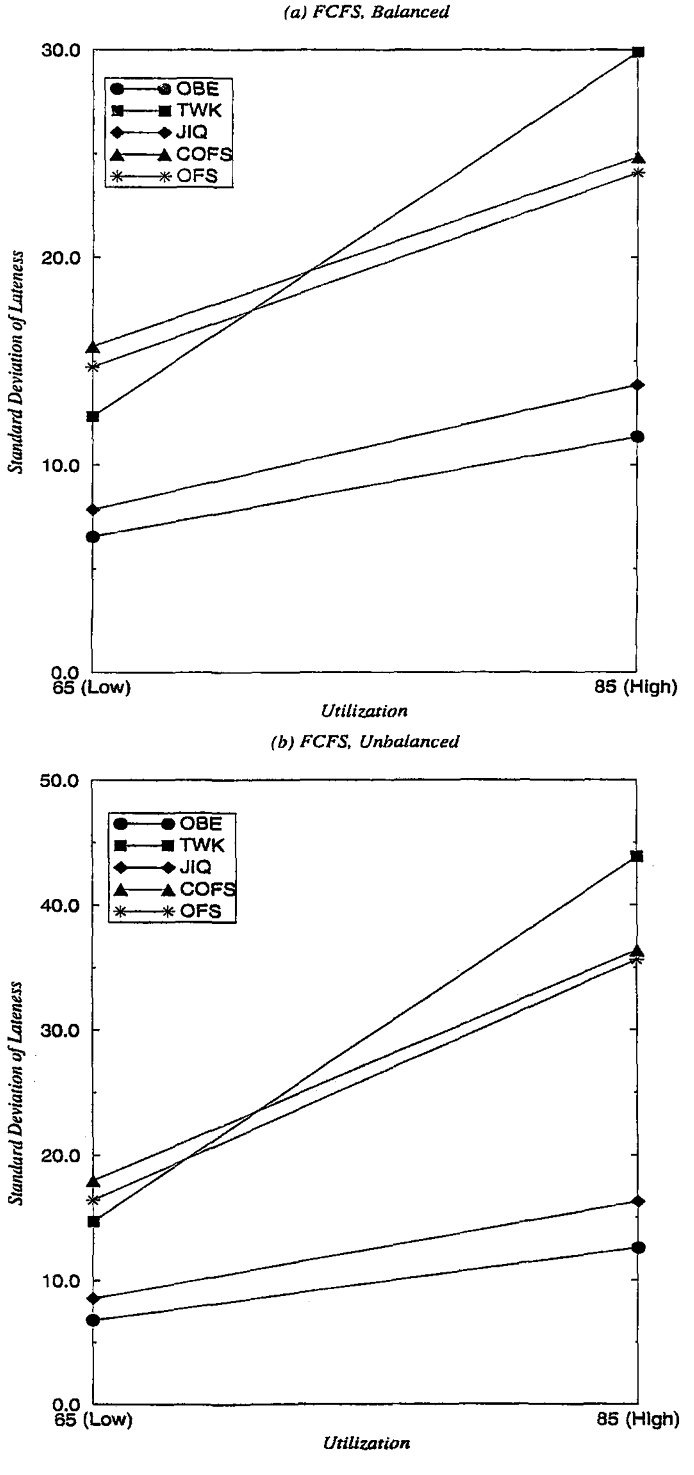


Figure 5.8: Standard Deviation of Lateness (STDL) versus Utilization for MOD

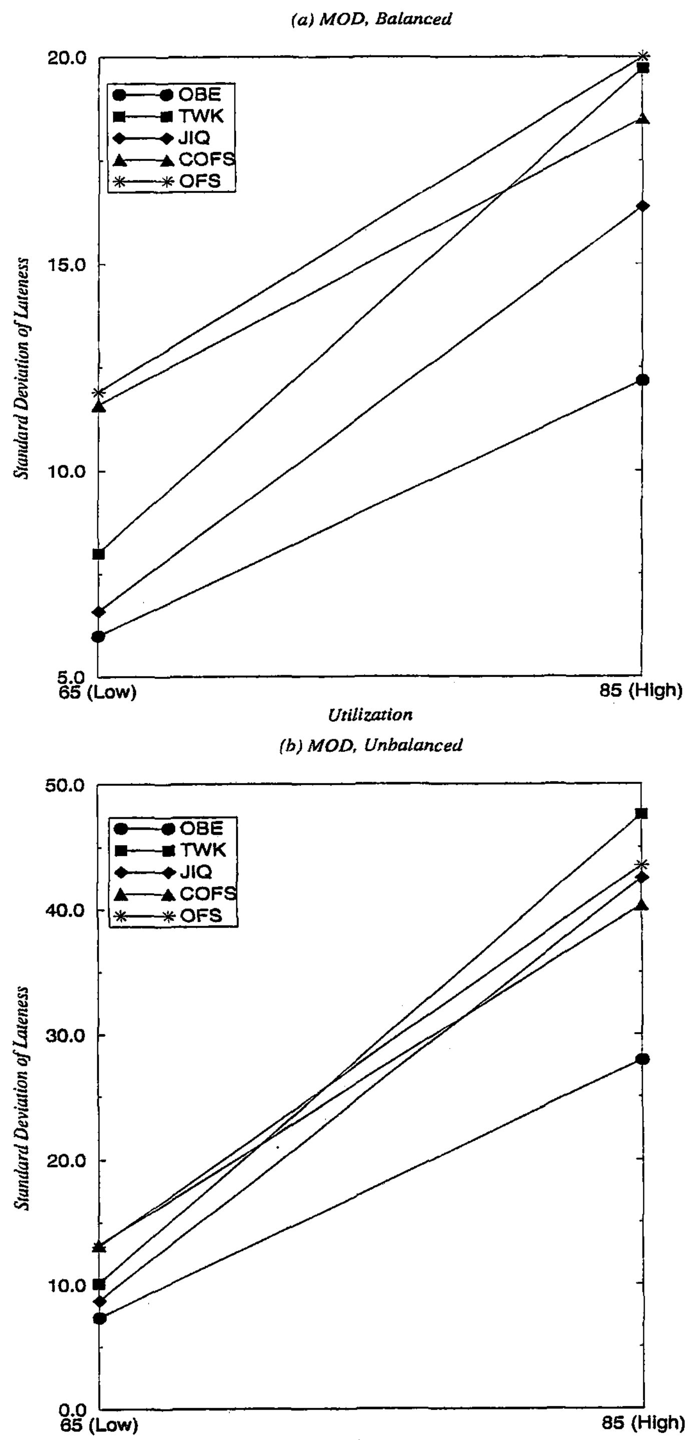


Figure 5.9: Standard Deviation of Lateness (STDL) versus Utilization for SPT

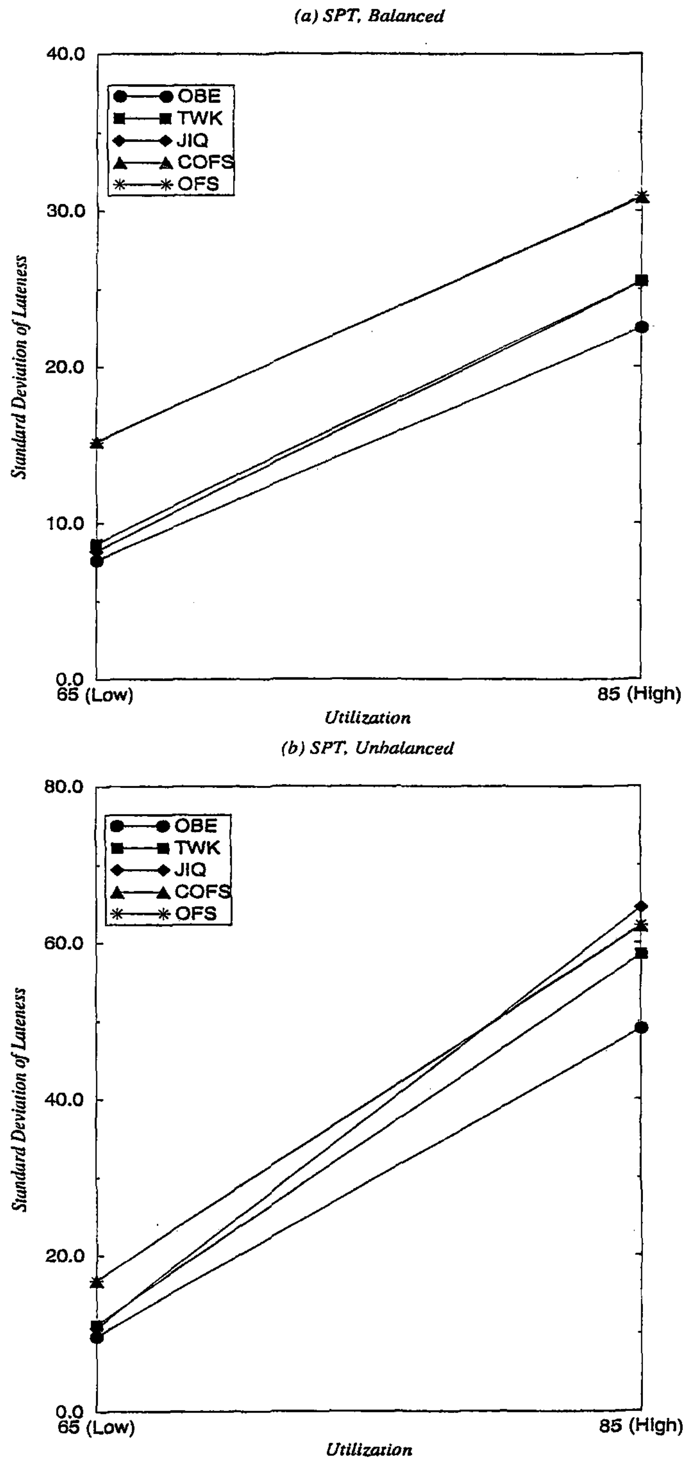
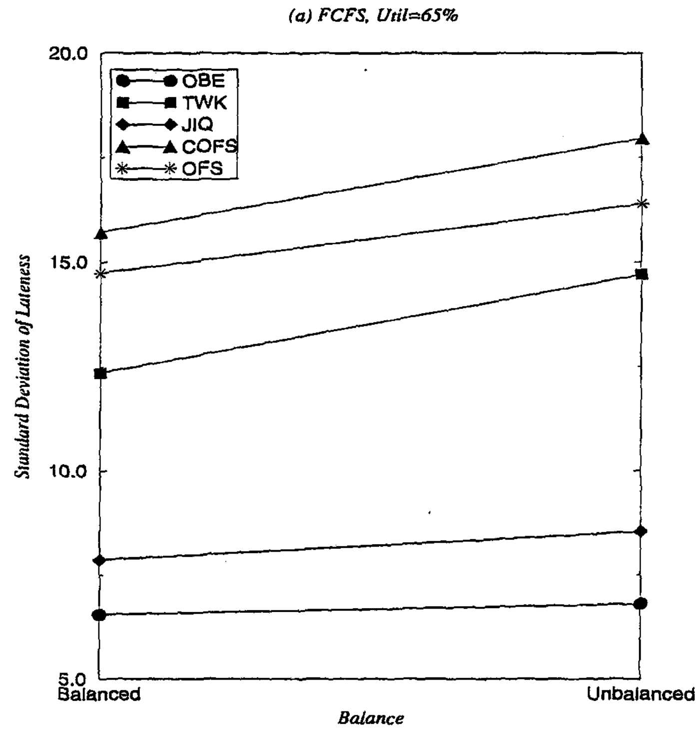


Figure 5.10: Standard Deviation of Lateness (STDL) versus Balance for FCFS



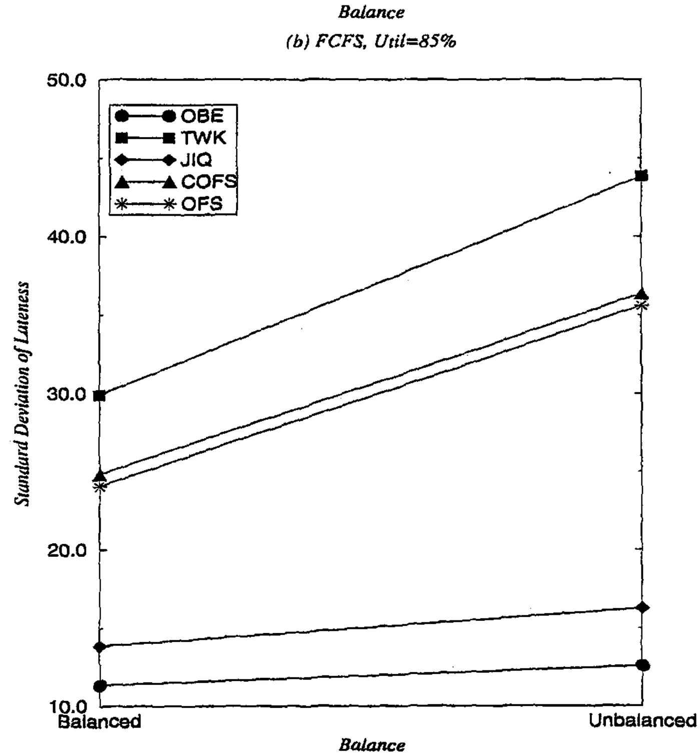


Figure 5.11: Standard Deviation of Lateness (STDL) versus Balance for MOD

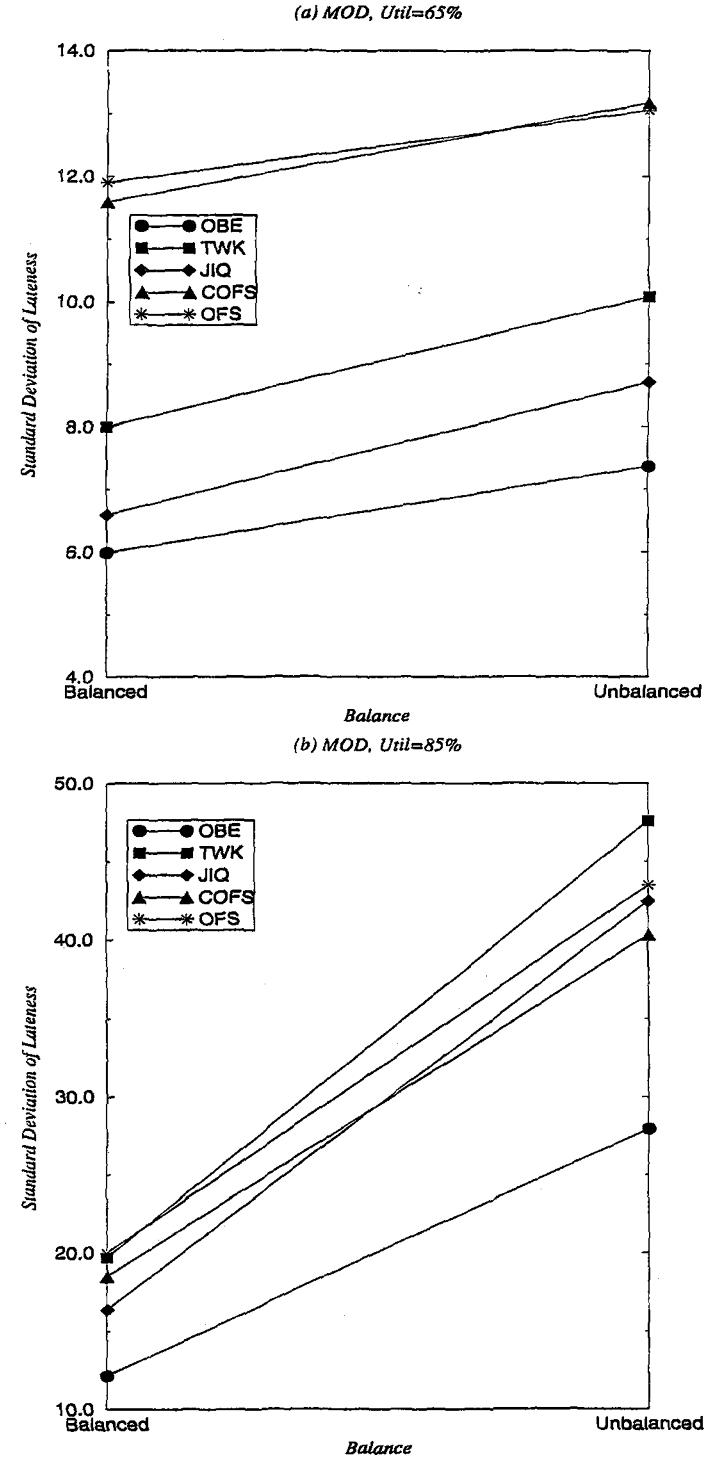


Figure 5.12: Standard Deviation of Lateness (STDL) versus Balance for SPT

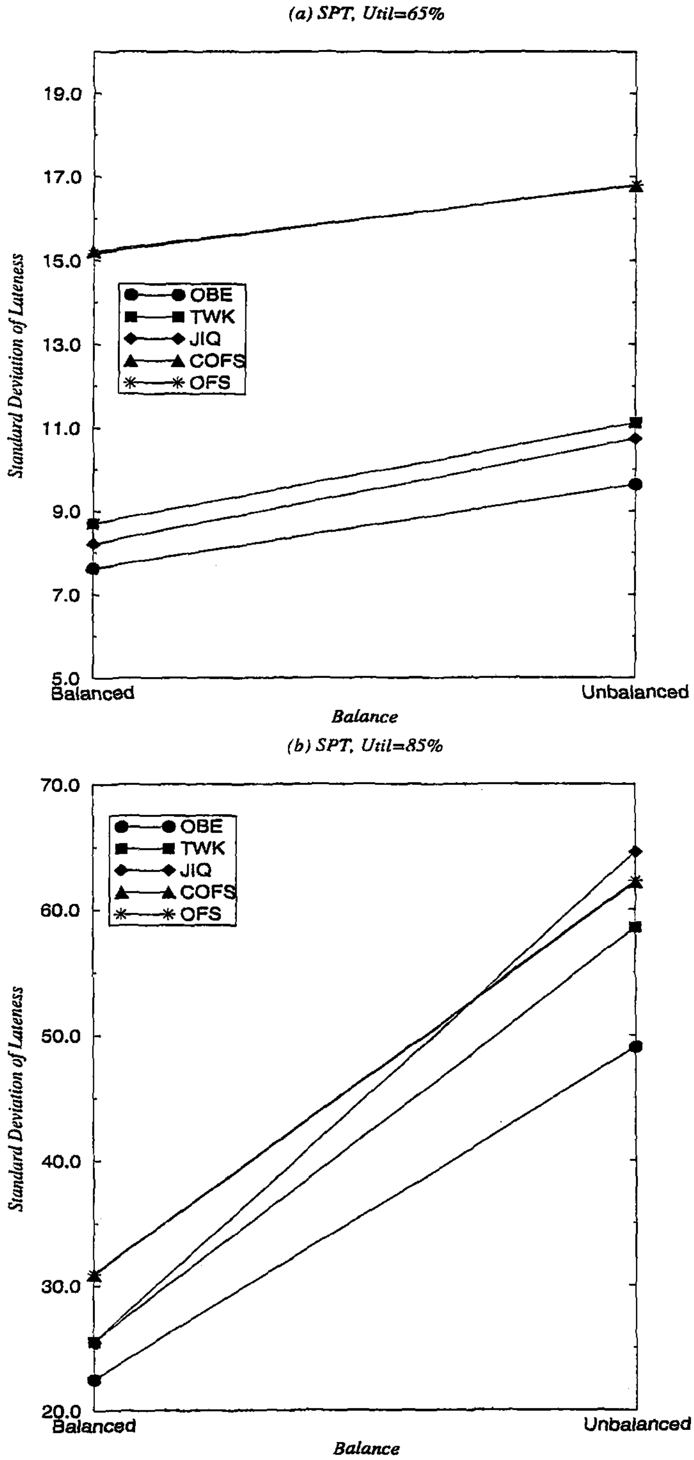


Table 5.16: Duncan's Multiple Range Tests for STDL

Levels	Mean	N	Method
All Factors Included			
A	25.4546	480	OFS
A	25.3725	480	COFS
A	24.1703	480	TWK
B	19.1416	480	JIQ
C	14.9658	480	**OBE**
Utilization=65%			
A	15.07308	240	COFS
B	14.67967	240	OFS
C	10.82333	240	TWK
D	8.44104	240	JIQ
E	7.32979	240	**OBE**
Utilization=85%			
A	37.517	240	TWK
A	36.229	240	OFS
A	35.672	240	COFS
B	29.842	240	JIQ
C	22.602	240	**OBE**
Balanced Shop			
A	19.4736	240	OFS
A	19.4573	240	COFS
B	17.3600	240	TWK
C	13.0612	240	JIQ
D	11.0341	240	**OBE**
Unbalanced Shop			
A	31.436	240	OFS
A	31.288	240	COFS
A	30.981	240	TWK
B	25.222	240	JIQ
C	18.897	240	**OBE**

5.2.3 Other Performance Measures

The results for the other performance measures are presented in Tables 5.1 - 5.4. These are: Mean Lateness (ML), Mean Tardiness (MT), Mean Squared Lateness (MSL), Mean Semi-Quadratic Lateness (MSQL), and Mean Flowtime (MF).

The following observations are made for these performance measures:

- There is no definite best method for ML criterion. That is, the relative performance of the flowtime estimation methods (as well as the best method) change as the experimental conditions are varied. We also note that the methods OFS and COFS which display the worst performances for MAL and STDL now perform the best for some conditions (see Table 5.17).
- In mean tardiness case, when the dispatching rule is FCFS, OBE is the best method in all the experimental conditions. However, when dispatching rule is either MOD or SPT, OBE yields the best performance for only the high utilization case. In the low utilization case, JIQ produces better tardiness values than the OBE. This improved performance of the JIQ is partly due to the fact that it overestimates the flowtimes of the jobs and hence, it results in early job completions with small tardiness values. This statement is also strengthened by the negative ML values obtained for JIQ.

Table 5.17: Best Flowtime Estimation Methods for ML

	Balanced Shop at Low Util.	*Unbalanced Shop at Low Util.*	*Balanced Shop at High Util.*	*Unbalanced Shop at High Util.*
FCFS	OFS	OFS	OBE	OBE
MOD	JIQ	TWK	OFS	COFS
SPT	JIQ	JIQ	COFS	TWK

- It is noticed that the results for MSL are similar (in terms of behavior of the rules) to the ones observed for STDL. This is because that both performance measures aim to quantify the variability of lateness.

- We have also observed that MSQL demonstrates a behavior which is a mix of MAL and MSL. This may be attributed to the fact that MSQL is a combination of MAL and MSL performance performance measures. However, we have also noted that when ML takes negative values, MSQL values also take quite smaller values. This is because that MSQL penalizes the early jobs only with the absolute value of the earliness whereas it penalizes the late jobs with the square of the lateness.

- Another observation is that exactly the same MF values are obtained for each flowtime estimation method when the dispatching rule is FCFS and SPT. This is because of the following reasons: (a) common random numbers are used in the experiments, and (b) FCFS and SPT do not utilize any flowtime allowance information and therefore their performance is completely independent of the flowtime estimation methods. But, slightly different values are observed for the MOD dispatching rule, even though these differences are of no practical importance.

Finally, we have also applied the ANOVA test to each of these performance measures. The resulting ANOVA tables are given in Appendix C. It is observed that all main factors and their interactions are significant. However, we also note some interesting exceptions. For example, flowtime estimation method (F) factor and its two way and higher interactions with the other factors are not significant for MF. This finding confirms the last observation we have made above.

Duncan's multiple range tests are also conducted for each performance measure. The results are given in Table 5.18. In general, OBE is the best method except for the MF performance measure.

Table 5.18: Duncan's Multiple Range Tests for Other Performance Measures

Levels		Mean	N	Method
Mean Lateness				
	A	2.3579	480	TWK
	B	0.3450	480	OFS
	B	0.0548	480	**OBE**
	C	-0.5639	480	JIQ
	C	-0.5653	480	COFS
Mean Tardiness				
	A	7.3592	480	TWK
	B	6.4578	480	OFS
	C	5.9132	480	COFS
	D	4.1056	480	JIQ
	E	3.4156	480	**OBE**
Mean Squared Lateness				
	A	1125.5	480	TWK
B	A	1049.5	480	OFS
B	A	1028.2	480	COFS
B		831.1	480	JIQ
	C	466.1	480	**OBE**
Mean Semi-Quadratic Lateness				
	A	1016.9	480	TWK
B	A	802.9	480	OFS
B		744.5	480	JIQ
B		714.4	480	COFS
	C	387.1	480	**OBE**
Mean Flowtime				
	A	26.4182	480	JIQ
	A	26.4181	480	OBE
	A	26.4084	480	COFS
	A	26.3402	480	OFS
	A	25.9595	480	**TWK**

5.2.4 Conclusions

We conclude this section with the following general observations:

- As the shop balance deteriorates or the the utilization level increases, the performances of the flowtime estimation methods are worsened. The differences in the relative performance of the methods also become more significant.
- Dispatching rules also affect the performance of the flowtime estimation methods. For example, FCFS rule leads to better MSL and STDL performance in the overall picture. This means that the precision of estimation methods can be made higher if FCFS rule is used.
- It is frequently reported in the literature that the shop congestion information is valuable in estimating flowtimes. This is also verified by the results of our experiments. But it has been also noted that the processing time information is more valuable when the shop is highly utilized and the dispatching is conducted with the SPT rule.
- In general, OBE is the best method for all performance measures except ML and MT. According to Duncan's grouping, there is no definite best method for ML. However, it is seen that JIQ becomes the best for MT in some cases.
- JIQ demonstrates the second best performance when compared to other methods. But its performance is not so good in highly loaded shop cases with the SPT dispatching rule.

5.3 Third Stage Results

In the third stage of our experiments, we have tested the sensitivity of flowtime estimation methods to changing shop conditions. These are: *machine breakdown*, *processing time variation* and *load variation* cases. During this stage, we have not generated new coefficients for the flowtime estimation methods. But instead, we have utilized the coefficients obtained for the second stage experiments. In this way, we aim to observe how the estimation methods are sensitive (or robust) to the unexpected changes in the shop conditions.

We did not compare the flowtime estimation methods for all shop conditions. Because our pilot experiments showed that system saturates (i.e. it becomes unstable) at high utilization level for machine breakdown and load variation cases. Hence, the third stage results were obtained for this two cases (machine breakdown and load variation) at low utilization level. Our preliminary runs also indicated that the effect of the processing time variation on the system performance is the minimal at low utilization rates. Hence, the simulation experiments were conducted for only the highly utilized shop conditions. The results of this stage are presented in Tables reftab:mbhigh - reftab:lv3.

5.3.1 Machine Breakdown Case

In this section, we discuss the results of the simulation experiments when machines in the system are broken according to some prespecified efficiency level (the proportion of time that the machines are up).

Even though we attempted to conduct the experiments for both the high utilization and low utilization cases, we observed that the system saturates even for the efficiency levels of 96% or above, when the system is at high utilization level (85%). Because the number of jobs in the system and the performance values of the system increase without any bound in each simulation experiment. Therefore, in order to get a general idea for the high utilization case, we only tested OBE and JIQ with the MOD dispatching rule. These two methods have been selected because they appeared to be the best methods in the second stage experiments. The results are given in Table 5.19.

It should be noted that since the system does saturate, the performance values given in Table 5.19 may not be the long term steady state estimates.

Nevertheless, we still detect that OBE performs better than JIQ for all performance measures except ML and MT. In fact, there exists no definite best method for the ML and MT measures. Their relative performance change as the experimental conditions are varied.

For the low utilization case, we have compared *all the flowtime estimation methods* for both balanced and unbalanced shop cases. The performance results for each of the dispatching rules are given in Tables 5.20 - 5.25. In general, the performance of the flowtime estimations methods deteriorate for all shop conditions, as the efficiency of the shop is decreased. Moreover, increasing the mean duration of breakdowns also negatively affects the performances for all criteria.

When the dispatching rule is FCFS, OBE performs better than other methods for MAL and STDL (Tables 5.20 - 5.25). OFS becomes the best method for ML except the case that the shop is not balanced and the efficiency level is 80%. For MOD and SPT rules, the results indicate that there is no single method which is the best for any specific performance measure. However, we observe that OBE competes with OFS and COFS methods. In all shop conditions, TWK performs worse than all other methods. This method makes use of no system information but job information and thus demonstrates the worst performance when compared to all other rules.

It is interesting to note the improved performance of OFS and COFS in the machine breakdown case. It is observed that OFS and COFS become the first or second or third best methods in many cases. This is partly due to the fact that they use flowtime information of the recently completed jobs. This information helps in capturing the changes of the shop conditions more effectively as compared to the information used by other methods. Thus, this means that when unexpected events occur in the system, the information obtained from the recently completed jobs is quite valuable.

The interactions of the flowtime estimation methods with the shop efficiency are depicted in Figures 5.13 - 5.16 for the MOD dispatching rule. The efficiency level 100% (i.e. no breakdowns case) has been also included in the figures so that the effects of machine breakdown can be compared with the results of second stage. It is observed that decreasing the efficiency level (i.e. more frequent breakdowns occur) negatively affects both MAL and STDL performances (as expected). In general, we observe that TWK method is the most sensitive method to the changes in the efficiency level of the system. This is because that TWK uses only job based information. Since the coefficients estimated for the second stage experiments are used, TWK provides flowtime estimates such that no breakdowns occur in the system. However, all the other methods utilizes shop information effectively and therefore, they consider the changes in shop conditions. The results indicate that, in general, OBE is the most robust method to the machine breakdown case.

5.3.2 Processing Time Variation

The results of the experiments are presented in Tables 5.26 - 5.31. In general, we observe that the performances of the flowtime estimation methods deteriorate as the processing time variation level (V) is increased.

The results for the FCFS rule indicate that OBE is definitely the best rule for all performance measures. However, when the dispatching rule is MOD, OBE performs better than other methods only for the STDL, MSL, MAL, and MSQL performance measures. In this case, OFS, COFS and TWK appear to be the best methods depending on the level of different processing time variation. Finally, we observe for the SPT rule that, OBE produces better results than other methods except the ML performance measure.

The interactions of the flowtime estimation methods with the processing time variation levels are also illustrated in Figures 5.17 - 5.18. It is noted that increasing the processing time variation affects the performances of the methods in the same rate except for the TWK and OFS methods. When the system is not balanced, OFS reacts more to the changes in processing time variation for both MAL and STDL. The same behavior is observed for TWK in the balanced shop case for only MAL performance.

Table 5.19: Performance Results for Machine Breakdown Under High Utilization (85%) Level

D Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
Balanced Shop at ϵ=96%								
D=5p	OBE	2.62	**20.28**	**4.77**	**460.27**	**6.92**	**437.32**	34.93
	JIQ	**1.42**	27.61	5.11	843.89	8.79	805.88	**34.53**
D=15p	OBE	3.91	**23.46**	**6.27**	**603.01**	**8.63**	**575.16**	**38.93**
	JIQ	**3.17**	31.31	7.02	1072.26	10.86	1029.38	38.98
Unbalanced Shop at ϵ=96%								
D=5p	OBE	**5.23**	**157.69**	**11.79**	**52915.52**	**18.35**	**52618.25**	64.44
	JIQ	8.45	206.19	16.33	90719.34	24.22	90540.43	**60.51**
D=15p	OBE	**6.78**	**155.88**	**13.56**	**46816.02**	**20.84**	**46459.56**	71.31
	JIQ	9.77	192.01	16.92	68945.85	24.08	68794.28	**62.12**
Balanced Shop at ϵ=98%								
D=5p	OBE	1.57	**15.56**	3.75	**262.89**	**5.92**	**241.68**	**30.34**
	JIQ	**−0.31**	21.20	**3.69**	488.19	7.69	447.72	30.39
D=15p	OBE	2.23	**18.12**	**4.50**	**355.55**	**6.77**	**332.14**	**32.28**
	JIQ	**0.45**	23.52	4.57	590.14	8.69	546.57	32.33
Unbalanced Shop at ϵ=98%								
D=5p	OBE	**0.29**	**54.99**	**5.47**	**5309.78**	**10.65**	**5197.46**	42.03
	JIQ	1.30	84.93	7.74	12301.56	14.17	12201.40	**41.37**
D=15p	OBE	**1.31**	**64.25**	**6.52**	**8079.86**	**11.73**	**7963.09**	44.87
	JIQ	2.55	92.82	9.04	14099.83	15.53	13995.02	**43.84**

Table 5.20: Machine Breakdown Results for
FCFS/Low Utilization (65%)/Balanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%		OBE	3.54	**10.91***	**5.60***	**131.93***	**7.66***	**111.57***	30.65
		TWK	14.27	19.29	15.67	583.43	17.07	570.29	30.65
	D=5p	JIQ	4.70	12.72	6.94	184.45	9.19	160.61	30.65
		COFS	−4.97	25.67	6.01	691.05	16.99	148.20	30.65
		OFS	**−0.49***	21.53	7.37	465.19	15.23	196.94	30.65
		OBE	5.26	**17.03***	**8.18***	**318.77***	**11.11***	**282.09***	38.59
		TWK	22.22	26.73	23.50	1220.84	24.78	1208.91	38.59
	D=15p	JIQ	6.89	18.76	9.81	401.12	12.72	361.52	38.59
		COFS	−8.09	37.34	8.38	1475.19	24.85	324.62	38.59
		OFS	**0.86***	29.64	10.97	881.74	21.09	450.33	38.59
80%		OBE	8.57	**15.63***	10.46	**318.92***	**12.35***	296.03	51.58
		TWK	35.21	32.34	35.69	2333.23	36.17	2329.63	51.58
	D=5p	JIQ	11.22	18.49	13.26	470.98	15.10	445.62	51.58
		COFS	−16.79	43.87	**6.42***	2272.70	29.63	**210.61***	51.58
		OFS	**0.99***	29.55	11.28	880.62	21.57	444.25	51.58
		OBE	11.92	**25.15***	15.48	**775.91***	**19.05***	711.75	66.82
		TWK	50.44	41.74	50.87	4354.75	51.30	4351.50	66.82
	D=15p	JIQ	15.48	27.93	18.77	1023.57	22.05	961.45	66.82
		COFS	−26.60	62.22	**8.80***	4703.74	44.20	**422.83***	66.82
		OFS	**4.54***	38.76	16.88	1530.01	29.21	914.80	66.82

Table 5.21: Machine Breakdown Results for
FCFS/Low Utilization (65%)/Unbalanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%		OBE	4.02	**11.42***	**6.04***	**147.17***	**8.07***	**126.38***	35.23
		TWK	17.31	23.76	18.94	889.30	20.57	871.44	35.23
	D=5p	JIQ	4.84	13.86	7.40	217.13	9.95	185.96	35.23
		COFS	−6.90	31.16	6.56	1045.77	20.01	183.65	35.23
		OFS	**0.52***	24.39	8.90	599.79	17.28	291.32	35.23
		OBE	5.73	**17.78***	8.71	**350.37***	**11.69***	**309.75***	43.89
		TWK	25.97	30.61	27.41	1644.93	28.86	1629.11	43.89
	D=15p	JIQ	6.86	19.97	10.24	448.29	13.63	394.61	43.89
		COFS	−11.29	43.90	**8.68**	2111.39	28.66	360.78	43.89
		OFS	**2.38***	32.01	12.69	1034.72	23.00	580.33	43.89
80%		OBE	**12.09**	**20.13***	14.39	**570.59***	**16.69***	533.18	87.82
		TWK	69.91	61.84	70.38	9954.84	70.85	9951.02	87.82
	D=5p	JIQ	18.07	25.22	19.92	1028.52	21.77	1001.07	87.82
		COFS	−61.66	107.78	**6.58***	20493.23	74.82	**381.29***	87.82
		OFS	13.77	52.73	27.10	3403.72	40.43	2611.44	87.82
		OBE	**15.25***	**27.85***	18.87	**1023.75***	**22.49***	951.60	101.11
		TWK	83.20	67.47	83.64	13030.48	84.08	13026.86	101.11
	D=15p	JIQ	21.35	32.62	24.53	1589.56	27.72	1523.02	101.11
		COFS	−80.31	129.79	**7.80***	33532.62	95.91	**499.08***	101.11
		OFS	18.94	57.02	32.23	4126.43	45.53	3322.97	101.11

Table 5.22: Machine Breakdown Results for
MOD/Low Utilization (65%)/Balanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%	*D=5p*	OBE	4.40	**11.19***	5.50	**145.75***	**6.60**	140.12	21.03
		TWK	6.55	14.64	7.63	261.97	8.71	255.67	**20.41***
		JIQ	3.55	12.19	5.10	163.59	6.65	155.26	21.31
		COFS	−1.51	15.78	**4.02***	252.11	9.55	**92.50**	22.64
		OFS	**−1.18***	15.99	4.16	258.92	9.50	99.92	22.55
	D=15p	OBE	7.28	**18.07***	8.55	**381.73**	9.82	**373.87**	25.78
		TWK	11.07	22.66	12.15	640.29	13.23	633.82	**24.93***
		JIQ	6.04	18.65	7.91	386.43	**9.78**	373.92	26.34
		COFS	−1.27	22.80	**6.27***	523.71	13.82	243.00	28.23
		OFS	**0.09***	22.76	6.84	520.03	13.59	274.12	27.84
80%	*D=5p*	OBE	9.92	21.09	10.63	559.27	**11.33**	555.35	30.52
		TWK	15.50	28.08	15.93	1061.49	16.37	1059.51	**29.37***
		JIQ	8.98	23.54	10.10	651.80	11.43	645.41	31.28
		COFS	−2.47	**19.99***	**4.64***	**411.48**	11.75	**178.34***	34.98
		OFS	**0.27***	20.75	5.59	437.84	11.45	251.90	33.93
	D=15p	OBE	16.13	28.80	17.05	1099.93	17.97	1092.99	40.51
		TWK	25.35	38.22	25.79	2133.03	26.22	2131.03	**39.22***
		JIQ	14.26	30.35	15.79	1137.68	17.32	1125.44	41.81
		COFS	−2.93	27.69	**7.52***	778.99	17.97	**342.67***	46.70
		OFS	**1.90***	**27.36**	9.52	**756.32**	**17.14**	478.15	45.40

Table 5.23: Machine Breakdown Results for
MOD/Low Utilization (65%)/Unbalanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%		OBE	4.84	**15.02***	6.04	**258.02***	**7.24***	250.02	22.77
		TWK	6.64	20.95	8.02	508.47	9.40	498.81	**22.00***
	D=5p	JIQ	3.90	18.19	5.69	368.56	7.48	357.73	23.05
		COFS	−1.45	18.51	**4.34***	350.91	10.13	**159.37***	24.72
		OFS	**−0.50***	18.54	4.73	351.39	9.95	194.15	24.26
		OBE	7.84	**21.15***	9.22	**517.93***	**10.60**	506.51	27.84
		TWK	11.31	27.04	12.67	878.88	14.02	869.29	**26.67***
	D=15p	JIQ	6.47	23.33	8.56	600.11	10.65	585.02	28.09
		COFS	−1.01	24.27	**6.52***	593.66	14.05	**294.21***	30.35
		OFS	**0.81***	24.28	7.33	595.29	13.84	364.82	29.99
80%		OBE	14.29	82.98	15.29	10979.27	**16.28**	10965.42	41.02
		TWK	22.45	101.83	22.96	17728.16	23.46	17725.50	**37.81***
	D=5p	JIQ	13.67	91.88	15.38	12400.27	17.09	12384.94	41.08
		COFS	**−0.74***	**61.47***	**8.36***	**6033.46***	17.46	**5567.01***	48.34
		OFS	5.45	86.03	12.11	12450.21	18.77	12128.56	47.02
		OBE	20.27	77.98	21.42	10216.06	**22.57**	10199.20	50.73
		TWK	31.24	94.20	31.76	13314.55	32.27	13311.82	**46.60***
	D=15p	JIQ	19.11	90.06	21.10	12244.02	23.08	12222.33	51.59
		COFS	**−1.08***	**62.49***	**10.83***	**5740.43***	22.73	**5080.94***	61.16
		OFS	7.54	75.30	15.16	8191.36	22.79	7837.68	57.13

Table 5.24: Machine Breakdown Results for
SPT/Low Utilization (65%)/Balanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%	*D=5p*	OBE	5.38	**13.91***	6.73	**224.64***	**8.08***	216.83	20.14
		TWK	6.22	15.37	7.65	278.56	9.08	269.47	20.14
		JIQ	3.87	14.98	6.10	242.26	8.34	227.32	20.14
		COFS	−2.19	22.93	**5.67***	535.17	13.53	**195.59***	20.14
		OFS	**−1.67***	22.58	5.83	517.17	13.33	201.99	20.14
	D=15p	OBE	8.65	**20.78***	10.17	**510.56***	**11.69***	500.54	24.63
		TWK	10.71	23.07	12.15	653.28	13.59	644.00	24.63
		JIQ	6.80	22.24	9.59	545.41	12.38	521.48	24.63
		COFS	−1.81	31.37	**8.56***	993.88	18.93	**431.48***	24.63
		OFS	**−0.71***	30.60	8.90	942.64	18.51	451.49	24.63
80%	*D=5p*	OBE	12.28	**26.26***	13.24	**866.20***	14.19	860.36	29.11
		TWK	15.19	28.89	15.83	1098.26	16.48	1095.01	29.11
		JIQ	10.05	28.36	12.07	935.47	**14.09***	919.69	29.11
		COFS	−2.86	35.26	**8.44***	1278.11	19.74	**643.24***	29.11
		OFS	**−1.29***	34.53	8.92	1221.06	19.13	676.69	29.11
	D=15p	OBE	19.30	**35.17***	20.57	**1631.59***	**21.84***	1621.18	38.79
		TWK	24.86	38.63	25.53	2139.07	26.19	2135.52	38.79
		JIQ	16.38	37.55	19.33	1703.06	22.28	1669.16	38.79
		COFS	−2.98	45.85	**12.90***	2132.43	28.78	**1055.47***	38.79
		OFS	**0.34***	44.18	13.93	1971.26	27.52	1141.49	38.79

Table 5.25: Machine Breakdown Results for
SPT/Low Utilization (65%)/Unbalanced Shop

ϵ	D Level	Methods	ML	STDL	MT	MSL	MAL	MSQL	MF
90%	*D=5p*	OBE	5.90	**19.22***	7.42	**425.17***	**8.94***	**413.75***	21.47
		TWK	7.13	21.74	8.62	551.75	10.11	541.92	21.47
		JIQ	4.36	21.46	**6.90**	506.51	9.45	487.62	21.47
		COFS	−0.29	27.04	6.91	756.26	14.11	430.26	21.47
		OFS	**0.18***	26.86	7.07	745.86	13.96	440.11	21.47
	D=15p	OBE	9.23	**24.93***	10.97	**722.99***	**12.71***	**707.66**	26.29
		TWK	11.96	28.66	13.44	993.80	14.93	983.92	26.29
		JIQ	7.41	27.95	10.62	863.06	13.83	832.25	26.29
		COFS	**0.75***	34.37	**10.05***	1202.37	19.34	710.93	26.29
		OFS	1.75	33.94	10.40	1175.41	19.05	737.82	26.29
80%	*D=5p*	OBE	18.21	**93.54***	19.42	**13215.85***	**20.62***	**13205.82***	37.22
		TWK	22.88	100.32	23.51	14925.52	24.15	14922.21	37.22
		JIQ	14.74	100.03	18.19	14543.78	21.64	14501.94	37.22
		COFS	**3.97***	102.11	**15.92***	14613.95	27.87	13629.89	37.22
		OFS	6.09	101.95	16.65	14625.33	27.20	13782.86	37.22
	D=15p	OBE	24.69	**93.40**	26.34	**13545.21***	**27.99***	**13525.72**	46.77
		TWK	32.43	101.44	33.09	15845.06	33.76	15841.40	46.77
		JIQ	20.83	100.69	25.21	15059.67	29.60	14991.13	46.77
		COFS	**4.99***	103.01	**20.33***	14939.49	35.68	13615.13	46.77
		OFS	8.72	102.49	21.66	14927.20	34.59	13890.89	46.77

Figure 5.13: Mean Absolute Lateness (MAL) versus Efficiency Levels for Balanced Shop

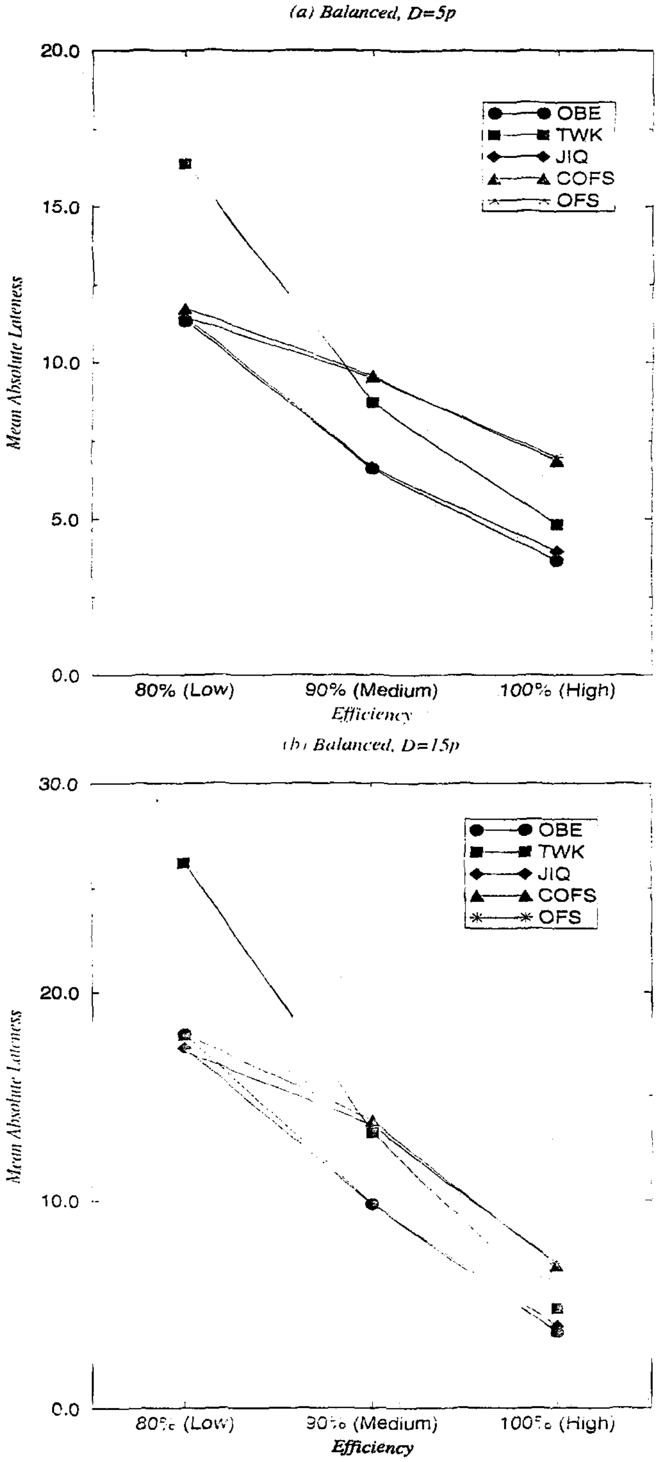


Figure 5.14: Standard Deviation of Lateness (STDL) versus Efficiency Levels for Balanced Shop

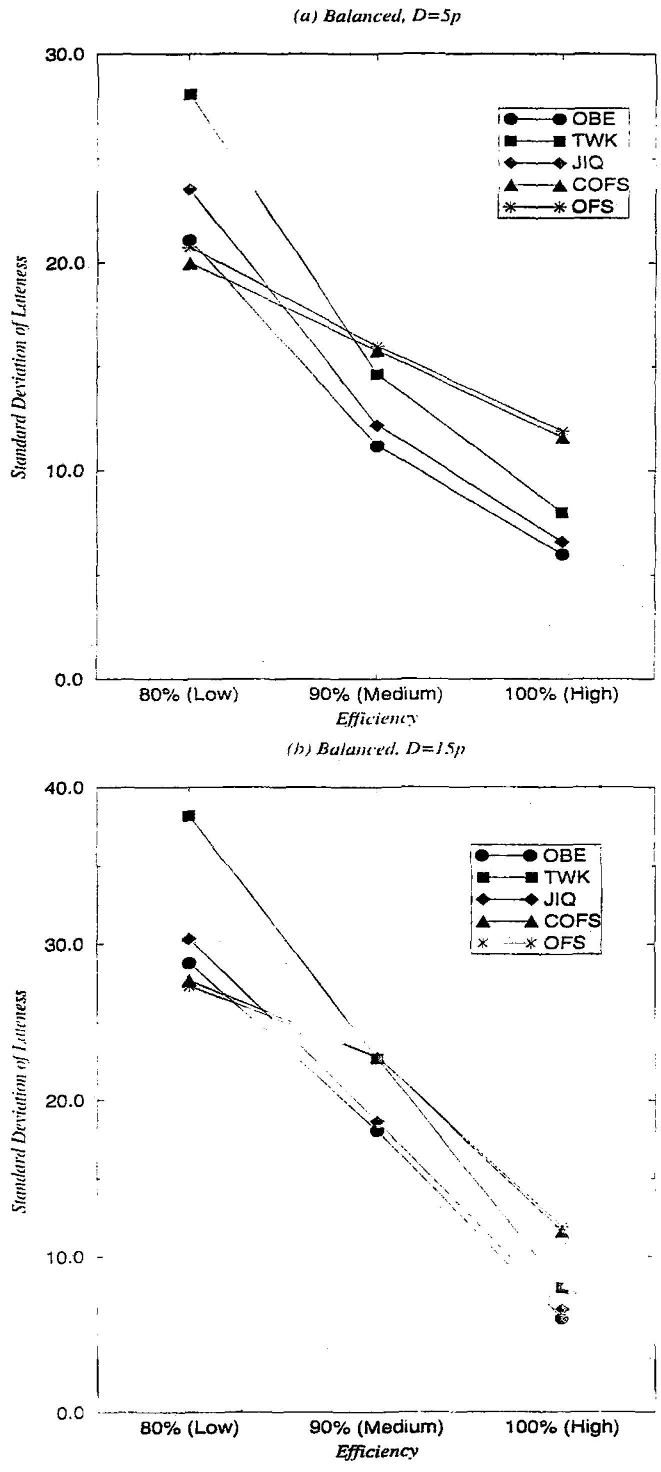


Figure 5.15: Mean Absolute Lateness (MAL) versus Efficiency Levels for Unbalanced Shop

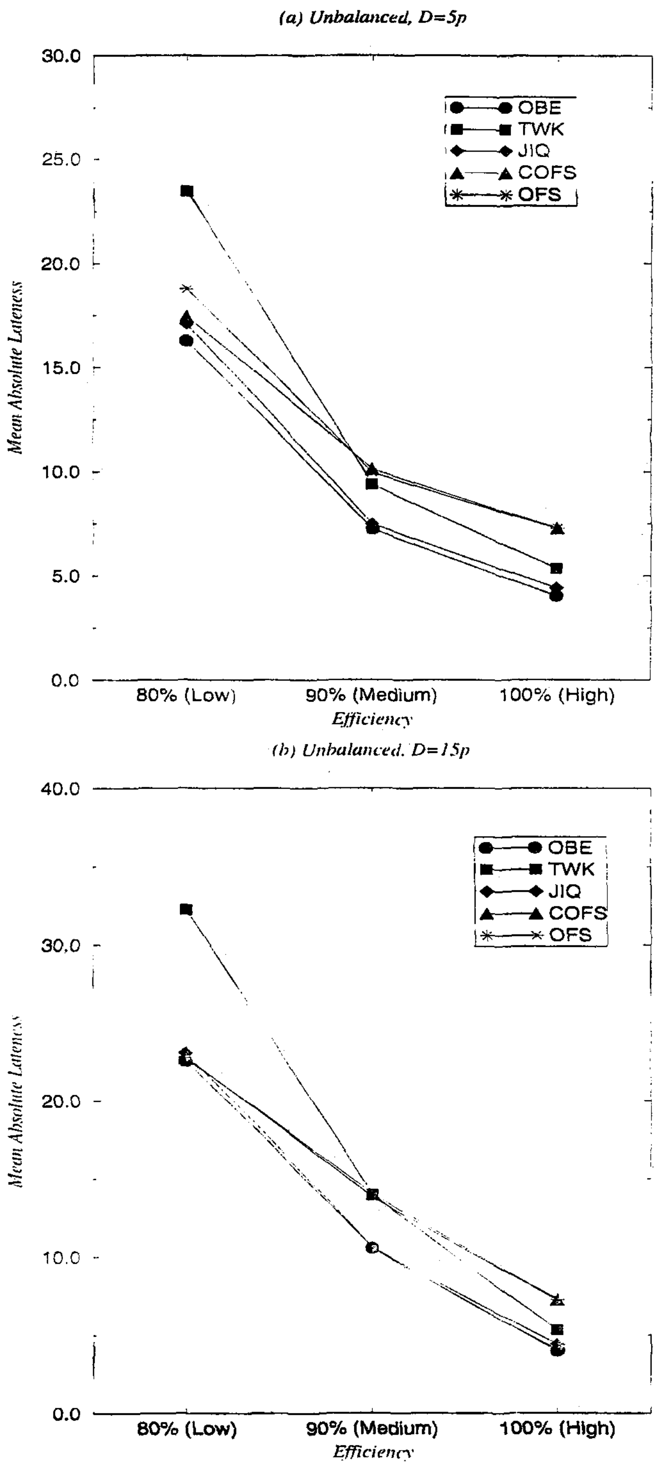


Figure 5.16: Standard Deviation of Lateness (STDL) versus Efficiency Levels for Unbalanced Shop

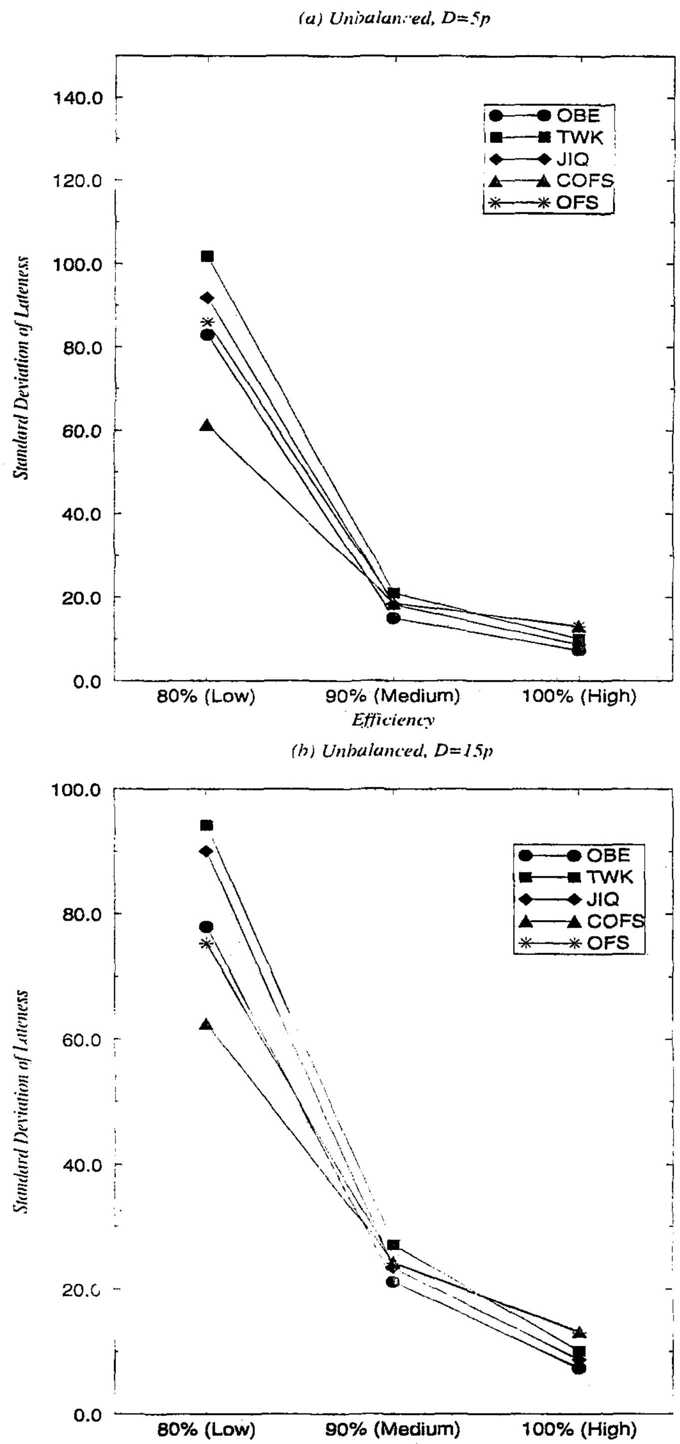


Table 5.26: Processing Time Variation Results for
FCFS / High Utilization (85%)/Balanced Shop

PV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
V=0.2	OBE	**0.48***	**11.54***	**4.14***	**135.41***	**7.80***	**79.20***	45.76
	TWK	9.70	30.04	16.75	1047.13	23.80	822.25	45.76
	JIQ	1.32	14.02	5.63	200.48	9.93	130.59	45.76
	COFS	−0.80	25.15	8.51	650.72	17.81	249.58	45.76
	OFS	1.28	24.25	9.59	597.28	17.89	322.90	45.76
V=0.4	OBE	**0.57***	**12.38***	**4.50***	**156.15***	**8.43***	**91.69***	48.18
	TWK	12.12	31.38	18.75	1207.14	25.38	996.38	48.18
	JIQ	1.58	14.90	6.07	277.41	10.55	150.63	48.18
	COFS	−1.53	26.88	8.72	753.58	19.96	268.13	48.18
	OFS	1.58	25.48	10.23	663.73	18.88	366.11	48.18
V=0.6	OBE	**0.72***	**13.41***	**4.99***	**182.95***	**9.26***	**108.54***	50.23
	TWK	14.17	32.45	20.39	1324.63	26.60	1128.92	50.23
	JIQ	1.85	15.89	6.58	259.20	11.30	173.12	50.23
	COFS	−1.84	28.34	9.09	835.45	20.02	296.08	50.23
	OFS	1.99	26.72	10.90	729.40	19.80	414.92	50.23

Table 5.27: Processing Time Variation Results for
FCFS / High Utilization (85%)/Unbalanced Shop

PV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
V=0.2	OBE	**0.42***	**12.97***	**4.61***	**174.64***	**8.81***	**100.07***	64.73
	TWK	17.23	44.61	27.17	2705.99	37.10	2265.07	64.73
	JIQ	1.46	16.79	6.66	292.43	11.86	186.90	64.73
	COFS	−3.20	37.59	11.42	1670.02	26.04	488.59	64.73
	OFS	5.23	36.14	16.14	1464.10	27.04	977.64	64.73
V=0.4	OBE	**0.55***	**13.79***	**4.99***	**197.82***	**9.44***	**113.91***	66.06
	TWK	18.58	45.52	28.31	2901.22	38.04	2469.81	66.06
	JIQ	1.55	17.32	6.90	312.32	12.25	200.65	66.06
	COFS	−3.95	38.87	11.50	1812.35	26.95	498.84	66.06
	OFS	5.72	36.70	16.64	1528.43	27.55	1043.46	66.06
V=0.6	OBE	**0.42***	**15.14***	**5.50***	**240.57***	**10.58***	**133.93***	73.72
	TWK	26.23	50.26	35.01	4056.77	43.79	3676.42	73.72
	JIQ	2.12	18.91	7.80	376.11	13.47	246.53	73.72
	COFS	−8.06	46.49	12.00	2919.42	32.07	591.06	73.72
	OFS	8.36	41.68	20.04	2103.90	31.72	1532.69	73.72

Table 5.28: Processing Time Variation Results for
MOD / High Utilization (85%)/Balanced Shop

PV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
V=0.2	OBE	0.80	**12.37***	2.97	**164.28***	**5.14***	**144.38***	26.94
	TWK	−0.83	19.88	3.75	423.17	8.33	354.43	**24.93***
	JIQ	−1.76	17.23	**2.61***	320.65	6.99	276.15	26.99
	COFS	−0.24	18.73	4.07	362.86	8.39	212.72	26.77
	OFS	**−0.06**	20.32	4.36	428.63	8.78	256.87	26.54
V=0.4	OBE	1.03	**13.19***	3.27	**184.58***	**5.51***	**163.19***	27.82
	TWK	**−0.04**	22.13	4.31	544.81	8.66	480.12	**25.73***
	JIQ	−1.47	17.74	**2.88***	337.92	7.22	292.85	27.74
	COFS	−0.23	19.36	4.26	387.17	8.75	238.39	27.94
	OFS	0.10	20.52	4.55	436.46	9.00	278.06	27.26
V=0.6	OBE	1.45	**14.67***	3.74	**237.26***	**6.03***	**214.06***	29.48
	TWK	0.95	23.40	5.01	608.89	9.08	548.10	**26.71***
	JIQ	−0.86	19.23	**3.41***	402.15	7.68	356.15	29.19
	COFS	**−0.23***	20.54	4.52	437.17	9.27	272.23	29.40
	OFS	0.42	22.58	5.02	536.16	9.62	363.07	29.12

Table 5.29: Processing Time Variation Results for
MOD / High Utilization (85%)/Unbalanced Shop

PV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
V=0.2	OBE	−2.17	**30.31***	**3.27***	**1374.39***	**8.70***	**1267.37***	34.24
	TWK	**−0.40***	47.28	5.79	3208.98	11.98	3096.39	**30.50***
	JIQ	−2.56	43.38	4.33	2748.22	11.21	2645.54	33.56
	COFS	1.22	41.44	6.05	2392.43	10.88	2197.14	32.47
	OFS	1.20	43.29	6.38	2540.49	11.55	2274.61	31.97
V=0.4	OBE	−1.63	**30.86***	**3.78***	**1395.62***	**9.19***	**1323.26***	35.94
	TWK	**0.28***	49.04	6.22	3360.91	12.16	3252.04	**31.18***
	JIQ	−2.03	44.43	4.71	3104.60	11.44	3003.12	34.62
	COFS	1.27	41.18	6.20	2285.60	11.12	2070.79	33.27
	OFS	1.77	47.21	7.00	3175.68	12.23	2904.39	33.27
V=0.6	OBE	−1.37	**31.83***	**3.94***	**1404.06***	**9.25***	**1397.45***	36.56
	TWK	1.85	54.50	7.31	4037.43	12.78	3938.93	**32.75***
	JIQ	**−1.22**	50.50	5.39	3821.59	12.01	3719.34	36.30
	COFS	1.47	47.25	6.94	3089.20	12.41	2837.74	35.98
	OFS	2.75	54.85	8.07	4507.03	13.39	4220.00	35.71

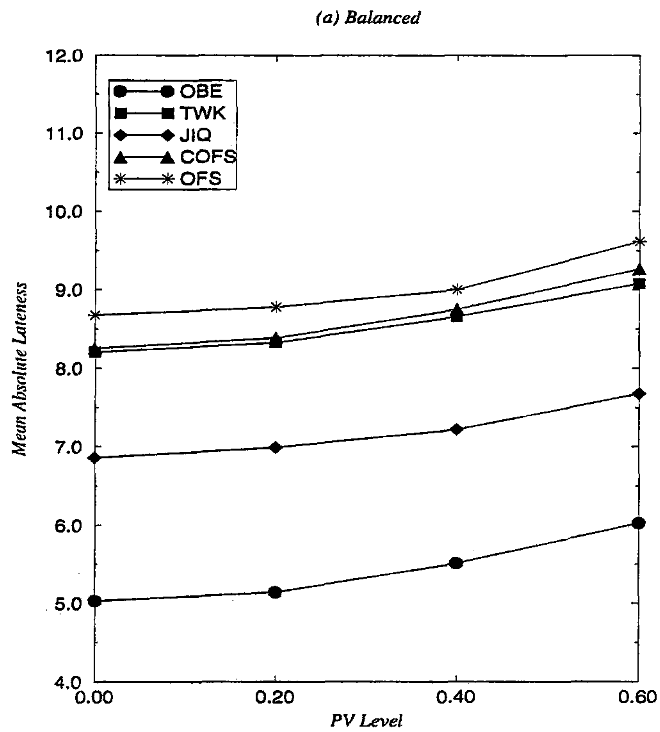
Table 5.30: Processing Time Variation Results for
SPT / High Utilization (85%)/Balanced Shop

PV Level	**Flowtime Estimation**	**ML**	**STDL**	**MT**	**MSL**	**MAL**	**MSQL**	**MF**
V=0.2	OBE	−1.09	**23.23***	**4.62***	**568.50***	**10.32***	**442.23***	22.56
	TWK	−0.74	26.53	5.25	746.82	11.23	654.00	22.56
	JIQ	−1.69	26.47	4.92	745.78	11.53	655.14	22.56
	COFS	**0.39***	31.93	7.50	1057.61	14.62	671.72	22.56
	OFS	0.55	32.04	7.58	1063.50	14.62	683.27	22.56
V=0.4	OBE	−0.84	**24.24***	**4.99***	**623.39***	**10.82***	**487.89***	23.35
	TWK	**0.04**	27.60	5.80	814.78	11.55	726.05	23.35
	JIQ	−1.12	27.58	5.39	814.44	11.90	724.68	23.35
	COFS	0.43	32.87	7.86	1124.23	15.28	727.03	23.35
	OFS	0.71	32.87	7.97	1123.84	15.23	741.13	23.05
V=0.6	OBE	−0.39	**26.36***	**5.54***	**734.26***	**11.48***	**587.94***	24.48
	TWK	1.17	30.10	6.67	973.40	12.17	888.18	24.48
	JIQ	**−0.30**	30.08	6.12	969.98	12.53	879.84	24.48
	COFS	0.63	35.33	8.42	1301.84	16.20	861.48	24.48
	OFS	1.09	35.31	8.60	1300.83	16.11	882.60	24.48

Table 5.31: Processing Time Variation Results for
SPT / High Utilization (85%)/Unbalanced Shop

PV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
V=0.2	OBE	−2.12	**50.26***	**6.73***	**3291.19***	**15.58***	**2780.97***	26.34
	TWK	**−1.07***	59.55	7.64	4825.02	16.35	4653.79	26.34
	JIQ	−1.41	59.53	7.58	4820.31	16.58	4635.22	26.34
	COFS	2.17	62.93	10.50	5131.64	18.82	4549.29	26.34
	OFS	2.33	63.05	10.57	5146.02	18.81	4571.23	26.34
V=0.4	OBE	−2.13	**50.96***	**7.01***	**3300.27***	**16.15***	**2733.83***	27.18
	TWK	**−0.22***	61.46	8.20	4909.33	16.63	4743.79	27.18
	JIQ	−0.54	61.43	8.15	4909.05	16.85	4725.49	27.18
	COFS	2.46	64.77	10.98	5223.45	19.51	4626.46	27.18
	OFS	2.70	64.87	11.09	5237.03	19.48	4652.27	27.18
V=0.6	OBE	−1.45	**61.45***	**8.06***	**5685.15***	**17.56**	**5053.35***	28.93
	TWK	1.52	71.77	9.55	8138.98	17.59	7982.09	28.93
	JIQ	**1.26***	71.72	9.51	8129.80	17.77	7961.41	28.93
	COFS	3.26	74.98	12.19	8394.22	21.12	7704.08	28.93
	OFS	3.65	75.06	12.35	8416.25	21.04	7747.91	28.93

Figure 5.17: Mean Absolute Lateness (MAL) versus Processing Time Variation (PV)



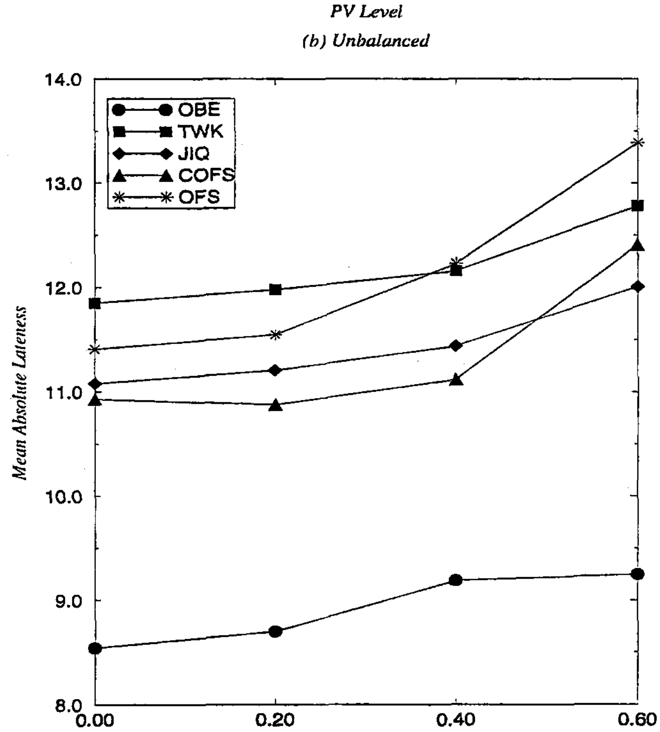
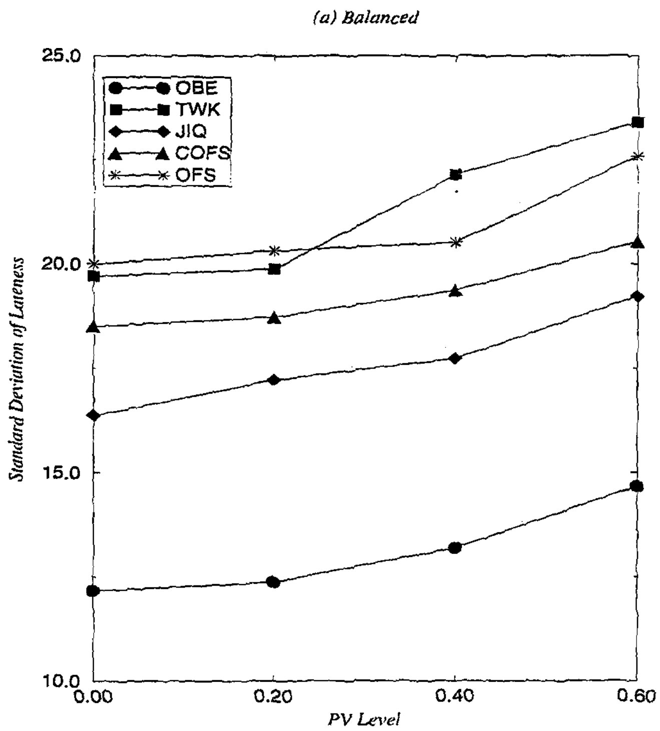


Figure 5.18: Standard Deviation of Lateness (STDL) versus Processing Time Variation (PV)



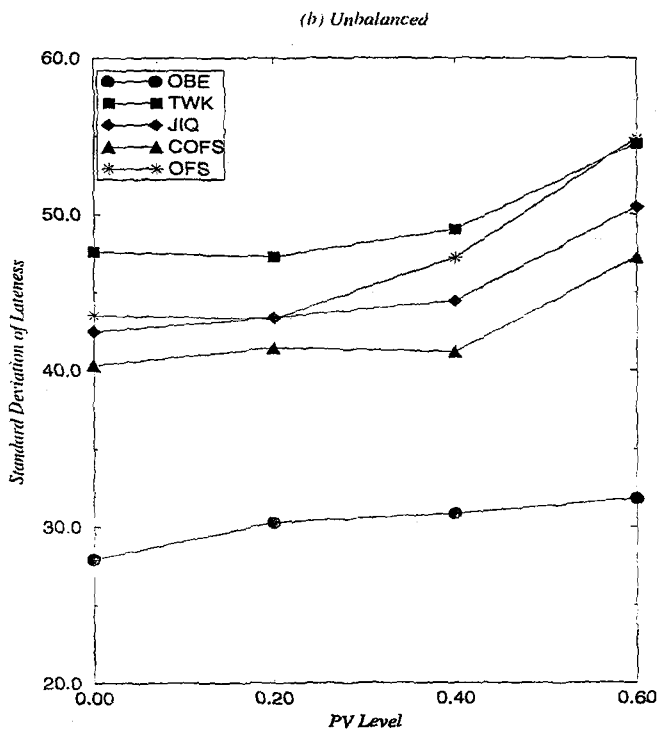


Table 5.32: Load Variation Results for
FCFS / Low Utilization (65%)

Balanced Shop								
LV Level	**Flowtime Estimation**	**ML**	**STDL**	**MT**	**MSL**	**MAL**	**MSQL**	**MF**
LV=10%	OBE	0.59	**6.52***	**2.47***	**43.09***	**4.35***	**28.82***	19.43
	TWK	3.05	12.53	6.11	170.71	9.17	137.46	19.43
	JIQ	0.93	7.86	3.17	62.95	5.41	44.68	19.43
	COFS	−1.18	15.90	4.58	258.23	10.35	73.92	19.43
	OFS	**−0.42***	14.78	4.84	219.89	10.10	83.42	19.43
LV=20%	OBE	0.55	**6.47***	**2.42***	**42.56***	**4.29***	**28.07***	19.11
	TWK	2.73	12.66	5.97	173.96	9.21	138.14	19.11
	JIQ	0.85	7.78	3.09	61.67	5.32	43.12	19.11
	COFS	−1.18	15.96	4.54	262.24	10.26	72.22	19.11
	OFS	**−0.40***	14.68	4.79	217.49	9.98	82.08	19.11
Unbalanced Shop								
LV Level	**Flowtime Estimation**	**ML**	**STDL**	**MT**	**MSL**	**MAL**	**MSQL**	**MF**
LV=10%	OBE	0.85	**6.75***	**2.67***	**46.76***	**4.50***	**32.24***	21.25
	TWK	3.33	14.74	6.99	236.46	10.64	189.67	21.25
	JIQ	0.86	8.49	3.34	73.43	5.81	50.75	21.25
	COFS	−1.44	18.05	4.99	335.96	11.42	89.59	21.25
	OFS	**−0.35***	16.45	5.39	272.88	11.14	108.58	21.25
LV=20%	OBE	0.80	**6.79***	**2.64***	**47.24***	**4.48***	**32.16***	21.23
	TWK	3.31	15.35	7.15	259.62	11.00	209.44	21.23
	JIQ	0.81	8.49	3.28	73.58	5.76	50.35	21.23
	COFS	−1.51	18.40	5.00	353.44	11, 51	91, 35	21.23
	OFS	**−0.17***	16.45	5.48	273.99	11.12	114.37	21.23

Table 5.33: Load Variation Results for
MOD / Low Utilization (65%)

LV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
Balanced Shop								
LV=10%	OBE	0.62	**6.04***	2.15	**37.49***	**3.68***	**30.34***	14.76
	TWK	0.67	8.10	2.76	67.56	4.85	53.12	**14.54***
	JIQ	**−0.05***	6.66	**1.95***	45.08	3.96	34.76	14.88
	COFS	−0.97	11.66	2.94	137.50	6.86	41.69	15.28
	OFS	−1.17	11.96	2.90	145.23	6.98	41.74	15.27
LV=20%	OBE	0.55	**5.96***	2.10	**36.46***	**3.65***	**29.28***	14.58
	TWK	0.49	8.19	2.70	69.57	4.90	53.94	**14.35***
	JIQ	**−0.12***	6.64	**1.91***	45.09	3.94	34.61	14.70
	COFS	−0.89	11.48	2.95	133.21	6.79	40.68	15.11
	OFS	−1.11	11.86	2.92	142.58	6.95	41.63	15.09
Unbalanced Shop								
LV Level	**Flowtime Estimation**	**ML**	**STDL**	**MT**	**MSL**	**MAL**	**MSQL**	**MF**
LV=10%	OBE	0.82	**7.40***	2.42	**57.11***	**4.01***	**48.17***	15.55
	TWK	**−0.07***	10.16	2.65	107.55	5.37	84.69	**15.30***
	JIQ	−0.29	8.79	**2.07***	80.85	4.42	67.15	15.69
	COFS	−1.35	13.24	3.00	178.40	7.35	54.42	16.21
	OFS	−1.11	13.07	3.10	173.45	7.31	62.97	16.13
LV=20%	OBE	0.75	**7.73***	2.39	**63.23***	**4.03***	**53.92***	15.43
	TWK	**−0.19**	10.76	2.68	123.55	5.55	98.70	**15.17***
	JIQ	−0.37	9.16	**2.05***	89.56	4.47	75.34	15.53
	COFS	−1.26	13.52	3.05	186.23	7.36	58.61	16.03
	OFS	−1.08	13.54	3.14	187.14	7.36	69.83	15.98

5.3.3 Load Variation

The results of the load variation case are given in Tables 5.32 - 5.34. It seems that the performance of the flowtime estimation methods are not affected considerably with respect to the second stage results. It is also noted that the performances of the flowtime estimation methods are not affected much from the increase in when the load variation level (LV) from 10% to 20%. This finding suggests that the system compensates itself in the long run and the long term system performances does not change significantly on the average. We should also note that the system can recover from the load variation easily for the low utilization. It is also observed that OBE performs, in general, better than the other estimation methods for all dispatching rules except the ML and MT performance measures.

5.3.4 Conclusions

We can conclude this section with the following general observations:

- In the machine breakdown case, the flowtime estimation methods are quite sensitive to the levels of efficiency and the mean duration of breakdowns. In general, OFS and COFS start to compete with OBE in this case.
- Processing time variation also affects the performances of the estimation methods. However, the relative performances of the methods are not much affected when compared to the second stage results.
- Load variation does not significantly influence the performances of methods. This is probably due to the fact that the system recovers itself from the variation during the long simulation runs when the utilization is at the low level.
- It has also been noticed that TWK is the most sensitive method to the variation in the system. This is because that it is the only method which

Table 5.34: Load Variation Results for SPT / Low Utilization (65%)

LV Level	Flowtime Estimation	ML	STDL	MT	MSL	MAL	MSQL	MF
Balanced Shop								
LV=10%	OBE	0.94	**7.75***	2.75	**62.12***	**4.56***	**52.31***	14.25
	TWK	0.32	8.85	2.86	80.06	5.40	61.34	14.25
	JIQ	**−0.26***	8.36	**2.40***	71.33	5.06	55.04	14.25
	COFS	−1.44	15.34	3.70	239.53	8.84	70.66	14.25
	OFS	−1.39	15.31	3.72	238.37	8.83	71.62	14.25
LV=20%	OBE	0.85	**7.71***	2.68	**61.64***	**4.50***	**51.83***	14.05
	TWK	**0.13***	8.90	2.77	81.56	5.42	61.73	14.05
	JIQ	−0.37	8.34	**2.33***	71.61	5.02	55.03	14.05
	COFS	−1.33	15.01	3.69	229.53	8.71	69.87	14.05
	OFS	−1.29	14.97	3.71	227.88	8.70	70.92	14.05
Unbalanced Shop								
LV Level	**Flowtime Estimation**	**ML**	**STDL**	**MT**	**MSL**	**MAL**	**MSQL**	**MF**
LV=10%	OBE	1.19	**9.69***	3.10	**98.38***	**5.01***	**85.58***	14.84
	TWK	0.50	11.19	3.18	130.16	5.85	109.47	14.84
	JIQ	**−0.15***	10.79	**2.70***	121.13	5.56	102.54	14.84
	COFS	−0.78	16.72	4.19	283.68	9.15	116.25	14.84
	OFS	−0.75	16.74	4.20	284.05	9.16	117.55	14.84
LV=20%	OBE	1.12	**9.96***	3.04	**105.36***	**4.97***	**92.48***	14.72
	TWK	0.38	11.68	3.17	144.92	5.95	122.97	14.72
	JIQ	**−0.23***	11.23	**2.69***	133.82	5.61	114.55	14.72
	COFS	−0.72	17.08	4.22	299.12	9.17	126.80	14.72
	OFS	−0.70	17.10	4.24	299.53	9.18	128.48	14.72

does not utilize shop based information.

- Finally, we note that OBE appeared to be, in general, the most robust method under all variations of system conditions.

Chapter 6

Conclusion

In this study, we proposed a new method for estimating the job flowtimes in a dynamic multi-machine job shop environment. The proposed method uses the detailed job, shop and route information for each operation of a job and produces flowtime estimates on an operational basis. The method considers explicitly the machine imbalance information in the estimation process. The jobs in the system are classified as relevant and irrelevant according to some simple rules for each dispatching rule. The relevant jobs information is also utilized by the proposed method.

A traditional job shop model was used in the simulation study. To test the performances of the flowtime estimation methods, we developed a full factorial design. It consisted of four factors (flowtime estimation method, dispatching rule, shop utilization and shop balance). The proposed method was compared with two popular methods (JIQ and TWK) and two recently proposed methods (COFS and OFS) in the literature. A wide variety of performance measures were used to compare the estimation methods.

The experimental study was composed of three main stages. In the first stage, we collected data and used these data in estimating the equations of the flowtime estimation methods. The performance of the methods were compared at the second stage. We also tested the sensitivity of the previous results to machine breakdown, processing time variation and system load variation in the third stage.

In the first stage, regression analysis indicated that the estimated equations for FCFS explain a larger proportion of variation of the flowtimes when compared to MOD and SPT rules. This is partly due to the fact that SPT and MOD create a more dynamic environment which makes it difficult to estimate the job flowtimes.

Second stage analysis showed that, as the shop balance deteriorated or the utilization level increased, the performances of the estimation methods were worsened. The experimental results also revealed that the proposed method (OBE) performed the best when compared to the other methods with some exceptions for mean lateness and mean tardiness measures. Duncan's Multiple Range test also reinforced the fact that OBE is, in the overall performance, the best method for all performance measures. In our experiments, JIQ yielded the second best performance.

In the third stage of experiments, we aimed to observe the sensitivity of the flowtime estimation methods to the unexpected changes in the shop. The results showed that the flowtime estimation performances are quite sensitive to the machine breakdown and processing time variations in the system but not so much sensitive to the load variations. In the machine breakdown case, COFS and OFS methods competed with OBE. Relative performances of the methods were not much influenced by the processing time variations. It was also observed that TWK method is the most sensitive method to the variations in the system parameters which is due to the reason that it uses only job related information.

We suggest the following further research topics based on the analyses made in this thesis:

- The proposed flowtime estimation method can be combined with a due date setting procedure to attain some due date performance objectives (i.e. minimization of costs or meeting some service level constraints, etc.)
- The proposed method gives an explosion of the total flowtime of a job with respect to each of its operations. This detailed information can be used in shop floor scheduling decisions such as rerouting of jobs, order review/release, expedition of jobs, or any other area which makes use of flowtime information.
- In the third stage analysis, the coefficients of the flowtime estimation methods were not regenerated for the new shop conditions. The methodology proposed in this study can be extended and tested in environments where there exist machine breakdowns, processing time variations and load variations.

Appendix A

Coefficients, R^2 Values and P-values of the Flowtime Estimation Methods

Table A.1: Coefficients, p-values and R^2 values for OBE/FCFS/Unbalanced Shop/High Utilization

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.0157	0.0452	1.1843	0.0001	0.0001	0.0001	0.9978
12	0.9846	0.1737	1.0434	0.0001	0.0001	0.0001	0.9816
13	0.9570	0.2849	0.8153	0.0001	0.0001	0.0001	0.9703
14	0.9527	0.2977	0.8646	0.0001	0.0001	0.0001	0.9604
15	0.9387	0.3646	0.8176	0.0001	0.0001	0.0001	0.9530
21	1.0256	0.0329	1.1859	0.0001	0.0001	0.0001	0.9942
22	0.9523	0.1289	1.0034	0.0001	0.0001	0.0001	0.9430
23	0.8998	0.1841	1.0741	0.0001	0.0001	0.0001	0.8960
24	0.8495	0.2101	1.0938	0.0001	0.0001	0.0001	0.8634
25	0.8115	0.2472	1.1091	0.0001	0.0001	0.0001	0.8211
31	1.0388	0.0332	1.1341	0.0001	0.0001	0.0001	0.9865
32	0.8875	0.1207	1.0425	0.0001	0.0001	0.0001	0.8745
33	0.7813	0.1562	1.0914	0.0001	0.0001	0.0001	0.8005
34	0.6556	0.2073	1.0911	0.0001	0.0001	0.0001	0.7198
35	0.5870	0.2251	1.1451	0.0001	0.0001	0.0001	0.6803
41	1.0502	0.0292	1.1723	0.0001	0.0001	0.0001	0.9798
42	0.8472	0.1101	1.0588	0.0001	0.0001	0.0001	0.8233
43	0.6878	0.1419	1.1672	0.0001	0.0001	0.0001	0.7265
44	0.5592	0.1618	1.2049	0.0001	0.0001	0.0001	0.6506
45	0.4482	0.1729	1.2938	0.0001	0.0001	0.0001	0.5962
51	1.0642	0.0284	1.1204	0.0001	0.0001	0.0001	0.9678
52	0.7555	0.0904	1.1797	0.0001	0.0001	0.0001	0.7560
53	0.5923	0.1227	1.1493	0.0001	0.0001	0.0001	0.6576
54	0.4319	0.1319	1.2748	0.0001	0.0001	0.0001	0.5942
55	0.3192	0.1284	1.4083	0.0001	0.0001	0.0001	0.5358

Table A.2: Coefficients, p-values and R^2 values for OBE/FCFS/Unbalanced Shop/Low Utilization

$$PF_{ji}^{k} = c_{1j}^{k} X_{1ji}^{k} + c_{2j}^{k} X_{2ji}^{k} + c_{3j}^{k} X_{3ji}^{k}$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.0694	0.0847	1.1877	0.0001	0.0001	0.0001	0.9679
12	0.9585	0.2881	1.1062	0.0001	0.0001	0.0001	0.9121
13	0.8921	0.4042	1.1124	0.0001	0.0001	0.0001	0.8675
14	0.8283	0.4876	1.1062	0.0001	0.0001	0.0001	0.8223
15	0.7797	0.5481	1.1548	0.0001	0.0001	0.0001	0.7956
21	1.0849	0.0650	1.1825	0.0001	0.0001	0.0001	0.9601
22	0.9422	0.2541	1.1115	0.0001	0.0001	0.0001	0.8779
23	0.8302	0.3674	1.0954	0.0001	0.0001	0.0001	0.8162
24	0.7496	0.4065	1.1231	0.0001	0.0001	0.0001	0.7651
25	0.6882	0.4580	1.0797	0.0001	0.0001	0.0001	0.7204
31	1.1084	0.0631	1.1683	0.0001	0.0001	0.0001	0.9415
32	0.9023	0.2046	1.0828	0.0001	0.0001	0.0001	0.8271
33	0.7017	0.3030	1.0975	0.0001	0.0001	0.0001	0.7563
34	0.5767	0.3404	1.1329	0.0001	0.0001	0.0001	0.7090
35	0.5056	0.3486	1.1666	0.0001	0.0001	0.0001	0.6601
41	1.1308	0.0562	1.1458	0.0001	0.0001	0.0001	0.9249
42	0.8718	0.1958	1.0757	0.0001	0.0001	0.0001	0.7896
43	0.6327	0.2487	1.1044	0.0001	0.0001	0.0001	0.7187
44	0.5184	0.2635	1.1448	0.0001	0.0001	0.0001	0.6738
45	0.4346	0.2573	1.2152	0.0001	0.0001	0.0001	0.6282
51	1.1698	0.0491	1.1288	0.0001	0.0001	0.0001	0.9095
52	0.7618	0.1802	1.0725	0.0001	0.0001	0.0001	0.7615
53	0.5126	0.2208	1.0833	0.0001	0.0001	0.0001	0.7028
54	0.3533	0.2214	1.1462	0.0001	0.0001	0.0001	0.6541
55	0.2677	0.2104	1.1781	0.0001	0.0001	0.0001	0.6182

Table A.3: Coefficients, p-values and R^2 values for OBE/FCFS/Balanced Shop/High Utilization

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.0402	0.0385	1.1862	0.0001	0.0001	0.0001	0.9879
2	0.9330	0.1373	1.0321	0.0001	0.0001	0.0001	0.9168
3	0.8437	0.2106	1.0206	0.0001	0.0001	0.0001	0.8514
4	0.7441	0.2854	1.0577	0.0001	0.0001	0.0001	0.7987
5	0.6880	0.3172	1.0560	0.0001	0.0001	0.0001	0.7556

Table A.4: Coefficients, p-values and R^2 values for OBE/FCFS/Balanced Shop/Low Utilization

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.1218	0.0631	1.1660	0.0001	0.0001	0.0001	0.9443
2	0.9207	0.2425	1.0809	0.0001	0.0001	0.0001	0.8379
3	0.7606	0.3488	1.0302	0.0001	0.0001	0.0001	0.7715
4	0.6440	0.3896	1.1308	0.0001	0.0001	0.0001	0.7389
5	0.5411	0.3753	1.1886	0.0001	0.0001	0.0001	0.6767

Table A.5: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #1

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	0.4108	0.8914	6.5311	0.0001	0.0001	0.0001	0.2786
12	0.0974	0.9075	12.7359	0.0279	0.0020	0.0001	0.1706
13	0.0611	0.6234	10.7296	0.0622	0.0077	0.0001	0.1448
14	0.0609	0.0666	9.3619	0.0002	0.5504	0.0001	0.3305
15	0.0919	0.3697	9.5595	0.0001	0.0029	0.0001	0.2518
21	0.7625	0.1431	4.2664	0.0001	0.2808	0.0001	0.2631
22	0.2314	0.2307	4.0489	0.0001	0.0001	0.0001	0.4963
23	0.2260	0.0645	4.4206	0.0001	0.2144	0.0001	0.4120
24	0.2055	0.0724	5.3438	0.0001	0.2078	0.0001	0.3470
25	0.1995	0.1323	5.3997	0.0001	0.0059	0.0001	0.3890
31	0.7532	0.2263	2.2479	0.0001	0.0001	0.0001	0.5951
32	0.3698	0.0745	2.8253	0.0001	0.0113	0.0001	0.5522
33	0.3055	0.0541	3.0800	0.0001	0.0394	0.0001	0.5227
34	0.2456	0.0651	3.0220	0.0001	0.0080	0.0001	0.4750
35	0.2652	0.1066	3.8658	0.0001	0.0013	0.0001	0.3496
41	0.8086	0.1448	1.9856	0.0001	0.0001	0.0001	0.6935
42	0.4384	0.1872	2.0988	0.0001	0.0001	0.0001	0.6420
43	0.3175	0.1260	2.5053	0.0001	0.0001	0.0001	0.5790
44	0.3031	0.0486	2.5539	0.0001	0.0079	0.0001	0.5142
45	0.2008	0.0714	2.5922	0.0001	0.0001	0.0001	0.5760
51	1.0548	0.1284	1.5756	0.0001	0.0001	0.0001	0.8003
52	0.5710	0.1068	1.9382	0.0001	0.0001	0.0001	0.6732
53	0.3610	0.1433	2.0131	0.0001	0.0001	0.0001	0.5635
54	0.2976	0.0686	2.2403	0.0001	0.0001	0.0001	0.4666
55	0.2292	0.0990	2.0378	0.0001	0.0001	0.0001	0.5702

Table A.6: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #2

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.0222	0.2046	5.8726	0.0001	0.2792	0.0001	0.3411
12	0.4371	0.6821	8.7100	0.0001	0.0001	0.0001	0.3833
13	0.2431	0.7082	9.1537	0.0001	0.0001	0.0001	0.2448
14	0.1807	0.4809	8.0476	0.0001	0.0001	0.0001	0.4120
15	0.2001	0.5690	8.5041	0.0001	0.0001	0.0001	0.3159
21	1.2560	0.2744	3.3448	0.0001	0.0128	0.0001	0.3743
22	0.4820	0.1906	3.5438	0.0001	0.0005	0.0001	0.4851
23	0.3115	0.1348	2.6075	0.0001	0.0004	0.0001	0.4794
24	0.3033	0.0470	5.3975	0.0001	0.3964	0.0001	0.4625
25	0.2807	0.0126	4.6104	0.0001	0.7248	0.0001	0.5619
31	1.2652	0.1939	1.8394	0.0001	0.0001	0.0001	0.7296
32	0.5940	0.2557	2.1692	0.0001	0.0001	0.0001	0.6713
33	0.5067	0.1118	2.9655	0.0001	0.0007	0.0001	0.5281
34	0.3306	0.2354	2.6764	0.0001	0.0001	0.0001	0.5785
35	0.3454	0.1065	3.1519	0.0001	0.0003	0.0001	0.4496
41	1.2434	0.0903	1.8448	0.0001	0.0032	0.0001	0.6149
42	0.6244	0.2014	1.8956	0.0001	0.0001	0.0001	0.6738
43	0.4545	0.2107	2.2330	0.0001	0.0001	0.0001	0.6032
44	0.3878	0.1816	2.1624	0.0001	0.0001	0.0001	0.5757
45	0.3380	0.1416	2.3611	0.0001	0.0001	0.0001	0.5630
51	1.2676	0.1588	1.4240	0.0001	0.0001	0.0001	0.8147
52	0.6629	0.1733	1.5654	0.0001	0.0001	0.0001	0.6876
53	0.4822	0.2329	1.7165	0.0001	0.0001	0.0001	0.6099
54	0.3602	0.1668	1.8697	0.0001	0.0001	0.0001	0.5753
55	0.2697	0.1622	1.8391	0.0001	0.0001	0.0001	0.5419

Table A.7: Coefficients. p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #3

$$PF^k_{ji} = c^k_{1j}X^k_{1ji} + c^k_{2j}X^k_{2ji} + c^k_{3j}X^k_{3ji}$$

jk	c^k_{1j}	c^k_{2j}	c^k_{3j}	p^k_{1j}	p^k_{2j}	p^k_{3j}	R^2
11	1.1666	0.1421	6.0546	0.0001	0.4343	0.0001	0.3752
12	0.5053	0.6771	6.8862	0.0001	0.0001	0.0001	0.5387
13	0.3288	0.3995	7.1260	0.0001	0.0001	0.0001	0.5467
14	0.2107	0.3291	8.6373	0.0001	0.0134	0.0001	0.3072
15	0.2451	0.5712	7.8127	0.0001	0.0001	0.0001	0.3680
21	1.2905	0.1779	2.7530	0.0001	0.0007	0.0001	0.6880
22	0.5793	0.1478	3.6801	0.0001	0.0235	0.0001	0.4469
23	0.3389	0.2593	2.6557	0.0001	0.0001	0.0001	0.4644
24	0.3931	0.0718	4.3414	0.0001	0.1351	0.0001	0.5024
25	0.3440	0.0064	4.5731	0.0001	0.8802	0.0001	0.5145
31	1.6622	0.2249	1.6729	0.0001	0.0001	0.0001	0.7375
32	0.6340	0.2196	2.0570	0.0001	0.0001	0.0001	0.7539
33	0.4867	0.1879	2.8645	0.0001	0.0001	0.0001	0.6285
34	0.3678	0.2140	2.3445	0.0001	0.0001	0.0001	0.6410
35	0.3659	0.1826	2.6703	0.0001	0.0001	0.0001	0.5709
41	1.4734	0.1915	1.5318	0.0001	0.0001	0.0001	0.7998
42	0.7243	0.2001	1.8384	0.0001	0.0001	0.0001	0.7305
43	0.5067	0.2115	2.0538	0.0001	0.0001	0.0001	0.6689
44	0.4085	0.1814	2.0458	0.0001	0.0001	0.0001	0.6126
45	0.3578	0.1517	2.3488	0.0001	0.0001	0.0001	0.5827
51	1.3251	0.1475	1.4610	0.0001	0.0001	0.0001	0.8095
52	0.6862	0.2082	1.5807	0.0001	0.0001	0.0001	0.6969
53	0.5054	0.2193	1.7320	0.0001	0.0001	0.0001	0.6182
54	0.3711	0.1713	1.8237	0.0001	0.0001	0.0001	0.6132
55	0.2657	0.2097	1.7815	0.0001	0.0001	0.0001	0.5562

Table A.8: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #4

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.3151	0.5223	5.8799	0.0001	0.0211	0.0001	0.2736
12	0.5610	0.6677	6.4624	0.0001	0.0001	0.0001	0.4629
13	0.3323	0.3963	7.5320	0.0001	0.0022	0.0001	0.3526
14	0.2211	0.3420	8.0988	0.0001	0.0001	0.0001	0.5424
15	0.2468	0.4517	7.4546	0.0001	0.0001	0.0001	0.5018
21	1.3542	0.2943	2.8471	0.0001	0.0008	0.0001	0.4673
22	0.6337	0.2403	4.8154	0.0001	0.0146	0.0001	0.3258
23	0.3436	0.2647	2.6596	0.0001	0.0001	0.0001	0.4595
24	0.3842	0.1240	4.0565	0.0001	0.0008	0.0001	0.6078
25	0.3300	0.0753	4.1560	0.0001	0.0166	0.0001	0.6311
31	1.5298	0.2348	1.6599	0.0001	0.0001	0.0001	0.8478
32	0.6748	0.2271	2.0581	0.0001	0.0001	0.0001	0.7291
33	0.5961	0.1816	2.6955	0.0001	0.0001	0.0001	0.6064
34	0.4432	0.1225	2.5126	0.0001	0.0001	0.0001	0.5440
35	0.3443	0.2094	2.5479	0.0001	0.0001	0.0001	0.6142
41	1.5839	0.1572	1.6208	0.0001	0.0001	0.0001	0.7084
42	0.7895	0.1614	1.8796	0.0001	0.0001	0.0001	0.7056
43	0.5925	0.2360	1.9973	0.0001	0.0001	0.0001	0.6326
44	0.3876	0.2163	1.9553	0.0001	0.0001	0.0001	0.6250
45	0.3472	0.1626	2.4165	0.0001	0.0001	0.0001	0.5899
51	1.4721	0.1395	1.4718	0.0001	0.0001	0.0001	0.7926
52	0.6895	0.2277	1.5646	0.0001	0.0001	0.0001	0.7117
53	0.5305	0.2323	1.6716	0.0001	0.0001	0.0001	0.6437
54	0.3653	0.1863	1.8496	0.0001	0.0001	0.0001	0.6253
55	0.2633	0.1906	1.8537	0.0001	0.0001	0.0001	0.5683

Table A.9: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #5

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.5906	0.0360	4.6932	0.0001	0.8089	0.0001	0.5071
12	0.6042	0.3629	6.5521	0.0001	0.0405	0.0001	0.2860
13	0.3334	0.5966	8.9862	0.0001	0.0007	0.0001	0.2786
14	0.2725	0.4130	7.0594	0.0001	0.0001	0.0001	0.5752
15	0.2560	0.5133	8.1981	0.0001	0.0001	0.0001	0.3756
21	1.9123	0.2953	2.3223	0.0001	0.0031	0.0001	0.4729
22	0.6875	0.0371	3.7312	0.0001	0.4409	0.0001	0.6355
23	0.4100	0.0961	2.6462	0.0001	0.0188	0.0001	0.4946
24	0.3803	0.1935	3.7471	0.0001	0.0001	0.0001	0.6244
25	0.3622	0.0442	4.2459	0.0001	0.2497	0.0001	0.5481
31	1.6214	0.1745	1.6890	0.0001	0.0001	0.0001	0.8160
32	0.7633	0.1718	1.9821	0.0001	0.0001	0.0001	0.7016
33	0.5987	0.1260	2.6361	0.0001	0.0001	0.0001	0.6291
34	0.4946	0.1564	2.5214	0.0001	0.0001	0.0001	0.5584
35	0.3489	0.2337	2.5201	0.0001	0.0001	0.0001	0.6058
41	1.6378	0.1604	1.5632	0.0001	0.0001	0.0001	0.8347
42	0.7769	0.1808	1.8402	0.0001	0.0001	0.0001	0.7368
43	0.5854	0.2190	1.8731	0.0001	0.0001	0.0001	0.6548
44	0.3881	0.2268	1.9399	0.0001	0.0001	0.0001	0.6246
45	0.3367	0.1605	2.2550	0.0001	0.0001	0.0001	0.6014
51	1.4452	0.1652	1.4605	0.0001	0.0001	0.0001	0.7932
52	0.7442	0.2046	1.5813	0.0001	0.0001	0.0001	0.7110
53	0.4922	0.2391	1.7356	0.0001	0.0001	0.0001	0.6407
54	0.3647	0.1942	1.7958	0.0001	0.0001	0.0001	0.5847
55	0.2764	0.1795	1.8315	0.0001	0.0001	0.0001	0.5506

Table A.10: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/High Utilization/ Iteration #6

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.4743	0.1967	4.1769	0.0001	0.0573	0.0001	0.6235
12	0.5050	0.9837	9.0873	0.0001	0.0003	0.0001	0.1714
13	0.3581	0.6316	8.3796	0.0001	0.0001	0.0001	0.5002
14	0.2669	0.3526	7.2160	0.0001	0.0001	0.0001	0.5251
15	0.2633	0.4824	7.6123	0.0001	0.0001	0.0001	0.5207
21	1.7711	0.1162	2.5904	0.0001	0.0301	0.0001	0.7254
22	0.7653	0.1292	3.4925	0.0001	0.0241	0.0001	0.5680
23	0.4005	0.1944	2.1849	0.0001	0.0001	0.0001	0.6583
24	0.3935	0.1659	3.8059	0.0001	0.0001	0.0001	0.6256
25	0.3423	0.1389	4.2318	0.0001	0.0001	0.0001	0.5970
31	1.6535	0.1864	1.6298	0.0001	0.0001	0.0001	0.8446
32	0.7469	0.1541	2.0553	0.0001	0.0001	0.0001	0.6989
33	0.5839	0.1110	2.7919	0.0001	0.0001	0.0001	0.6385
34	0.4578	0.1829	2.4253	0.0001	0.0001	0.0001	0.5785
35	0.3658	0.2474	2.6304	0.0001	0.0001	0.0001	0.4867
41	1.6340	0.1829	1.5930	0.0001	0.0001	0.0001	0.7907
42	0.7832	0.2071	1.7831	0.0001	0.0001	0.0001	0.7236
43	0.5873	0.2437	1.9941	0.0001	0.0001	0.0001	0.6564
44	0.3873	0.2140	2.0258	0.0001	0.0001	0.0001	0.6091
45	0.3840	0.1738	2.2151	0.0001	0.0001	0.0001	0.6008
51	1.4705	0.1676	1.5121	0.0001	0.0001	0.0001	0.7993
52	0.7006	0.2178	1.5861	0.0001	0.0001	0.0001	0.7177
53	0.4600	0.2676	1.7138	0.0001	0.0001	0.0001	0.6216
54	0.3148	0.2379	1.7069	0.0001	0.0001	0.0001	0.6061
55	0.2727	0.2045	1.7935	0.0001	0.0001	0.0001	0.5465

Table A.11: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/ Iteration #1

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	0.8983	0.2702	1.7313	0.0001	0.0001	0.0001	0.6025
12	0.4467	0.2347	2.0625	0.0001	0.0001	0.0001	0.5970
13	0.2962	0.2253	2.2126	0.0001	0.0001	0.0001	0.5695
14	0.1830	0.2475	2.3250	0.0001	0.0001	0.0001	0.5760
15	0.2088	0.2004	2.2615	0.0001	0.0001	0.0001	0.5444
21	1.0039	0.1708	1.6054	0.0001	0.0001	0.0001	0.6664
22	0.4917	0.2686	1.6724	0.0001	0.0001	0.0001	0.6268
23	0.2538	0.2520	1.7902	0.0001	0.0001	0.0001	0.6806
24	0.2588	0.2654	1.8734	0.0001	0.0001	0.0001	0.5537
25	0.2048	0.1798	1.7860	0.0001	0.0001	0.0001	0.6406
31	0.9931	0.1115	1.4674	0.0001	0.0001	0.0001	0.7164
32	0.5404	0.2642	1.5100	0.0001	0.0001	0.0001	0.6815
33	0.3190	0.2104	1.6131	0.0001	0.0001	0.0001	0.6881
34	0.2832	0.1786	1.5806	0.0001	0.0001	0.0001	0.6385
35	0.2074	0.1560	1.6515	0.0001	0.0001	0.0001	0.6275
41	0.9713	0.1595	1.3636	0.0001	0.0001	0.0001	0.7525
42	0.4788	0.2032	1.4303	0.0001	0.0001	0.0001	0.7216
43	0.3202	0.1515	1.4699	0.0001	0.0001	0.0001	0.6697
44	0.2058	0.1823	1.4539	0.0001	0.0001	0.0001	0.6418
45	0.1897	0.1761	1.5315	0.0001	0.0001	0.0001	0.6457
51	1.2269	0.1147	1.2845	0.0001	0.0001	0.0001	0.7812
52	0.4141	0.1812	1.3003	0.0001	0.0001	0.0001	0.7410
53	0.2655	0.1885	1.3182	0.0001	0.0001	0.0001	0.7023
54	0.2418	0.1678	1.3920	0.0001	0.0001	0.0001	0.6914
55	0.1732	0.1243	1.4243	0.0001	0.0001	0.0001	0.6598

Table A.12: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/ Iteration #2

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.3847	0.2614	1.5298	0.0001	0.0001	0.0001	0.7238
12	0.5339	0.3481	1.8778	0.0001	0.0001	0.0001	0.6190
13	0.4018	0.2821	1.8937	0.0001	0.0001	0.0001	0.7159
14	0.2442	0.2438	2.2269	0.0001	0.0001	0.0001	0.6139
15	0.2937	0.1499	2.1448	0.0001	0.0001	0.0001	0.5697
21	1.3385	0.1566	1.5421	0.0001	0.0001	0.0001	0.7612
22	0.5990	0.2567	1.6674	0.0001	0.0001	0.0001	0.7137
23	0.2953	0.2656	1.5863	0.0001	0.0001	0.0001	0.6633
24	0.3295	0.2631	1.8474	0.0001	0.0001	0.0001	0.6131
25	0.2253	0.2477	1.6887	0.0001	0.0001	0.0001	0.6223
31	1.4268	0.1623	1.3223	0.0001	0.0001	0.0001	0.7978
32	0.6664	0.2664	1.3769	0.0001	0.0001	0.0001	0.7178
33	0.3922	0.2493	1.5210	0.0001	0.0001	0.0001	0.7010
34	0.3375	0.2102	1.5297	0.0001	0.0001	0.0001	0.6558
35	0.2207	0.1830	1.5613	0.0001	0.0001	0.0001	0.6587
41	1.2080	0.1399	1.3556	0.0001	0.0001	0.0001	0.7892
42	0.5855	0.2130	1.3578	0.0001	0.0001	0.0001	0.7334
43	0.3221	0.2085	1.3692	0.0001	0.0001	0.0001	0.6961
44	0.2195	0.1799	1.3782	0.0001	0.0001	0.0001	0.7095
45	0.1991	0.1880	1.4387	0.0001	0.0001	0.0001	0.6959
51	1.4947	0.1059	1.2520	0.0001	0.0001	0.0001	0.8041
52	0.4578	0.1982	1.2302	0.0001	0.0001	0.0001	0.7480
53	0.3572	0.1965	1.2841	0.0001	0.0001	0.0001	0.7187
54	0.2472	0.1865	1.2948	0.0001	0.0001	0.0001	0.7188
55	0.1592	0.1683	1.3291	0.0001	0.0001	0.0001	0.6904

Table A.13: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/Iteration #3

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.7701	0.2325	1.4624	0.0001	0.0001	0.0001	0.7393
12	0.6585	0.2882	1.8749	0.0001	0.0001	0.0001	0.6556
13	0.4766	0.3010	1.8625	0.0001	0.0001	0.0001	0.6666
14	0.2835	0.2702	2.0569	0.0001	0.0001	0.0001	0.6273
15	0.3039	0.1860	2.0471	0.0001	0.0001	0.0001	0.6204
21	1.6099	0.1678	1.5128	0.0001	0.0001	0.0001	0.7584
22	0.6715	0.2633	1.6954	0.0001	0.0001	0.0001	0.6990
23	0.3074	0.2609	1.5816	0.0001	0.0001	0.0001	0.6784
24	0.3658	0.2622	1.8067	0.0001	0.0001	0.0001	0.6306
25	0.2273	0.2436	1.6938	0.0001	0.0001	0.0001	0.6818
31	1.5544	0.1479	1.3297	0.0001	0.0001	0.0001	0.8250
32	0.5951	0.2674	1.4141	0.0001	0.0001	0.0001	0.7238
33	0.4549	0.2368	1.5062	0.0001	0.0001	0.0001	0.6877
34	0.3437	0.2417	1.4553	0.0001	0.0001	0.0001	0.6931
35	0.2303	0.2111	1.5185	0.0001	0.0001	0.0001	0.6904
41	1.3659	0.1515	1.3198	0.0001	0.0001	0.0001	0.8060
42	0.6526	0.1837	1.3903	0.0001	0.0001	0.0001	0.7401
43	0.2998	0.2238	1.3566	0.0001	0.0001	0.0001	0.7092
44	0.2569	0.1884	1.3906	0.0001	0.0001	0.0001	0.6924
45	0.1852	0.2002	1.4214	0.0001	0.0001	0.0001	0.7027
51	1.4312	0.1145	1.2546	0.0001	0.0001	0.0001	0.8120
52	0.5110	0.1866	1.2516	0.0001	0.0001	0.0001	0.7445
53	0.3867	0.1829	1.2846	0.0001	0.0001	0.0001	0.7156
54	0.2319	0.1906	1.2816	0.0001	0.0001	0.0001	0.7125
55	0.1624	0.1720	1.3162	0.0001	0.0001	0.0001	0.6910

Table A.14: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/ Iteration #4

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.8461	0.2115	1.5502	0.0001	0.0001	0.0001	0.7486
12	0.6835	0.3189	1.7354	0.0001	0.0001	0.0001	0.7266
13	0.5158	0.2939	1.7647	0.0001	0.0001	0.0001	0.7436
14	0.2844	0.2684	1.9623	0.0001	0.0001	0.0001	0.6830
15	0.2968	0.2107	1.9412	0.0001	0.0001	0.0001	0.6525
21	1.6155	0.1919	1.4910	0.0001	0.0001	0.0001	0.8058
22	0.7679	0.2813	1.5945	0.0001	0.0001	0.0001	0.7451
23	0.2983	0.2690	1.5360	0.0001	0.0001	0.0001	0.7034
24	0.3708	0.2849	1.7966	0.0001	0.0001	0.0001	0.6297
25	0.2440	0.2908	1.6603	0.0001	0.0001	0.0001	0.6005
31	1.6323	0.1405	1.3407	0.0001	0.0001	0.0001	0.8064
32	0.6743	0.2731	1.3633	0.0001	0.0001	0.0001	0.7240
33	0.4629	0.2558	1.4953	0.0001	0.0001	0.0001	0.6786
34	0.3550	0.2547	1.4757	0.0001	0.0001	0.0001	0.6771
35	0.2399	0.2213	1.4915	0.0001	0.0001	0.0001	0.6903
41	1.3709	0.1261	1.3484	0.0001	0.0001	0.0001	0.8074
42	0.6683	0.2244	1.3084	0.0001	0.0001	0.0001	0.7600
43	0.3449	0.2082	1.3960	0.0001	0.0001	0.0001	0.6976
44	0.2450	0.1790	1.3980	0.0001	0.0001	0.0001	0.6991
45	0.2024	0.2121	1.4423	0.0001	0.0001	0.0001	0.6963
51	1.4531	0.1076	1.2530	0.0001	0.0001	0.0001	0.8004
52	0.5479	0.2082	1.2366	0.0001	0.0001	0.0001	0.7395
53	0.3682	0.1825	1.2949	0.0001	0.0001	0.0001	0.7153
54	0.2438	0.1861	1.3106	0.0001	0.0001	0.0001	0.7170
55	0.1758	0.1559	1.3404	0.0001	0.0001	0.0001	0.7048

Table A.15: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/ Iteration #5

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.8700	0.2360	1.5561	0.0001	0.0001	0.0001	0.7401
12	0.7019	0.2350	1.7763	0.0001	0.0001	0.0001	0.7440
13	0.5311	0.2760	1.7775	0.0001	0.0001	0.0001	0.7386
14	0.2625	0.2733	1.9419	0.0001	0.0001	0.0001	0.6998
15	0.2934	0.1960	1.9716	0.0001	0.0001	0.0001	0.6727
21	1.6293	0.1737	1.6351	0.0001	0.0001	0.0001	0.6709
22	0.7547	0.2764	1.6710	0.0001	0.0001	0.0001	0.7028
23	0.3292	0.2468	1.5624	0.0001	0.0001	0.0001	0.6696
24	0.3818	0.2776	1.7676	0.0001	0.0001	0.0001	0.6286
25	0.2366	0.2883	1.6766	0.0001	0.0001	0.0001	0.6644
31	1.5009	0.1658	1.3522	0.0001	0.0001	0.0001	0.8021
32	0.6454	0.2772	1.3698	0.0001	0.0001	0.0001	0.7359
33	0.4236	0.2680	1.5065	0.0001	0.0001	0.0001	0.6992
34	0.3621	0.2651	1.4562	0.0001	0.0001	0.0001	0.6921
35	0.2385	0.2304	1.4611	0.0001	0.0001	0.0001	0.7063
41	1.4776	0.1400	1.3291	0.0001	0.0001	0.0001	0.7865
42	0.6419	0.2341	1.3399	0.0001	0.0001	0.0001	0.7513
43	0.3746	0.2268	1.3789	0.0001	0.0001	0.0001	0.6958
44	0.2389	0.1939	1.4112	0.0001	0.0001	0.0001	0.7032
45	0.1903	0.2270	1.4277	0.0001	0.0001	0.0001	0.7011
51	1.4193	0.1132	1.2655	0.0001	0.0001	0.0001	0.7926
52	0.5049	0.1920	1.2275	0.0001	0.0001	0.0001	0.7597
53	0.3663	0.1819	1.2870	0.0001	0.0001	0.0001	0.7187
54	0.2230	0.1914	1.3142	0.0001	0.0001	0.0001	0.7129
55	0.1661	0.1675	1.3084	0.0001	0.0001	0.0001	0.6950

Table A.16: Coefficients, p-values and R^2 values for OBE/MOD/Unbalanced Shop/Low Utilization/ Iteration #6

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	1.9954	0.2714	1.5607	0.0001	0.0001	0.0001	0.6212
12	0.7604	0.2331	1.8298	0.0001	0.0001	0.0001	0.7212
13	0.5487	0.3142	1.7555	0.0001	0.0001	0.0001	0.7157
14	0.2772	0.2439	1.9548	0.0001	0.0001	0.0001	0.6921
15	0.2891	0.2060	1.9566	0.0001	0.0001	0.0001	0.6741
21	1.7471	0.1886	1.5489	0.0001	0.0001	0.0001	0.6858
22	0.8222	0.2188	1.6485	0.0001	0.0001	0.0001	0.6885
23	0.3394	0.2480	1.5287	0.0001	0.0001	0.0001	0.6618
24	0.4012	0.2759	1.7430	0.0001	0.0001	0.0001	0.6535
25	0.2474	0.2594	1.6028	0.0001	0.0001	0.0001	0.6903
31	1.5244	0.1523	1.3591	0.0001	0.0001	0.0001	0.8099
32	0.6503	0.2680	1.4069	0.0001	0.0001	0.0001	0.7234
33	0.4644	0.2704	1.5175	0.0001	0.0001	0.0001	0.7029
34	0.3472	0.2563	1.4778	0.0001	0.0001	0.0001	0.6921
35	0.2450	0.2331	1.4745	0.0001	0.0001	0.0001	0.6876
41	1.4719	0.1608	1.2966	0.0001	0.0001	0.0001	0.7977
42	0.6193	0.2274	1.3389	0.0001	0.0001	0.0001	0.7669
43	0.3384	0.2285	1.4155	0.0001	0.0001	0.0001	0.6993
44	0.2328	0.1991	1.3947	0.0001	0.0001	0.0001	0.7055
45	0.1981	0.2320	1.4207	0.0001	0.0001	0.0001	0.7066
51	1.4986	0.1213	1.2361	0.0001	0.0001	0.0001	0.8100
52	0.5010	0.1955	1.2262	0.0001	0.0001	0.0001	0.7636
53	0.3403	0.1689	1.3099	0.0001	0.0001	0.0001	0.7025
54	0.2103	0.1866	1.3052	0.0001	0.0001	0.0001	0.7166
55	0.1672	0.1485	1.3107	0.0001	0.0001	0.0001	0.7003

Table A.17: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/High Utilization Iteration #1

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	0.7755	0.1740	2.6172	0.0001	0.0134	0.0001	0.3213
2	0.3030	0.1334	2.9270	0.0001	0.0001	0.0001	0.5829
3	0.2816	0.0922	3.0670	0.0001	0.0087	0.0001	0.4445
4	0.1942	0.0959	2.9052	0.0001	0.0001	0.0001	0.5428
5	0.1740	0.1082	2.8702	0.0001	0.0001	0.0001	0.5317

Table A.18: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/Low Utilization Iteration #1

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.0474	0.1378	1.4702	0.0001	0.0001	0.0001	0.7064
2	0.4793	0.2483	1.5352	0.0001	0.0001	0.0001	0.7011
3	0.2847	0.2222	1.6555	0.0001	0.0001	0.0001	0.6445
4	0.2184	0.2094	1.5421	0.0001	0.0001	0.0001	0.6618
5	0.2000	0.1780	1.6512	0.0001	0.0001	0.0001	0.6170

Table A.19: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/High Utilization Iteration #2

$$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$$

k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.3499	0.3906	2.1042	0.0001	0.0001	0.0001	0.3793
2	0.3624	0.0918	3.5593	0.0001	0.2149	0.0001	0.2541
3	0.3430	0.1205	2.9213	0.0001	0.0001	0.0001	0.5843
4	0.2585	0.1642	2.6165	0.0001	0.0001	0.0001	0.6405
5	0.2950	0.0680	2.6720	0.0001	0.0031	0.0001	0.5376

Table A.20: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/Low Utilization Iteration #2

$$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$$

k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.4846	0.1589	1.4076	0.0001	0.0001	0.0001	0.7801
2	0.5885	0.2453	1.4779	0.0001	0.0001	0.0001	0.7240
3	0.3784	0.2607	1.4814	0.0001	0.0001	0.0001	0.6852
4	0.2732	0.2261	1.5146	0.0001	0.0001	0.0001	0.6875
5	0.2602	0.2039	1.5558	0.0001	0.0001	0.0001	0.6313

Table A.21: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/High Utilization Iteration #3

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.7749	0.3656	2.0329	0.0001	0.0001	0.0001	0.4335
2	0.5748	0.1689	2.6979	0.0001	0.0001	0.0001	0.6273
3	0.4636	0.1025	2.7809	0.0001	0.0024	0.0001	0.5296
4	0.3229	0.1228	2.7724	0.0001	0.0001	0.0001	0.5950
5	0.2740	0.1227	2.6556	0.0001	0.0001	0.0001	0.5684

Table A.22: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/Low Utilization Iteration #3

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.7186	0.1618	1.3727	0.0001	0.0001	0.0001	0.7969
2	0.6648	0.2737	1.4562	0.0001	0.0001	0.0001	0.7319
3	0.4293	0.2713	1.4586	0.0001	0.0001	0.0001	0.7271
4	0.2635	0.2288	1.6082	0.0001	0.0001	0.0001	0.6337
5	0.2195	0.2087	1.5298	0.0001	0.0001	0.0001	0.6587

Table A.23: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/High Utilization Iteration #4

$$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$$

k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.8643	0.1520	1.8487	0.0001	0.0001	0.0001	0.7867
2	0.7161	0.1823	2.2712	0.0001	0.0001	0.0001	0.7074
3	0.4868	0.2449	2.3125	0.0001	0.0001	0.0001	0.7134
4	0.3366	0.1874	2.5058	0.0001	0.0001	0.0001	0.6078
5	0.3252	0.1662	2.5330	0.0001	0.0001	0.0001	0.5426

Table A.24: Coefficients, p-values and R^2 values for OBE/MOD/Balanced Shop/Low Utilization Iteration #4

$$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$$

k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.6073	0.1618	1.4070	0.0001	0.0001	0.0001	0.8101
2	0.7112	0.2499	1.4285	0.0001	0.0001	0.0001	0.7493
3	0.4835	0.2649	1.4779	0.0001	0.0001	0.0001	0.7027
4	0.2967	0.2183	1.5114	0.0001	0.0001	0.0001	0.6785
5	0.2739	0.2151	1.4724	0.0001	0.0001	0.0001	0.6789

Table A.25: Coefficients, p-values and R^2 values for
OBE/MOD/Balanced Shop/High Utilization
Iteration #5

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.6612	0.3030	1.9358	0.0001	0.0001	0.0001	0.6906
2	0.6739	0.1812	2.2913	0.0001	0.0001	0.0001	0.7180
3	0.5053	0.2363	2.5561	0.0001	0.0001	0.0001	0.5073
4	0.3536	0.1500	2.4487	0.0001	0.0001	0.0001	0.6778
5	0.3206	0.1191	2.7801	0.0001	0.0001	0.0001	0.5501

Table A.26: Coefficients, p-values and R^2 values for
OBE/MOD/Balanced Shop/Low Utilization
Iteration #5

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.7627	0.1416	1.3558	0.0001	0.0001	0.0001	0.7932
2	0.7011	0.2352	1.4888	0.0001	0.0001	0.0001	0.7442
3	0.4215	0.2489	1.4761	0.0001	0.0001	0.0001	0.7155
4	0.2791	0.2524	1.4590	0.0001	0.0001	0.0001	0.6681
5	0.2410	0.2476	1.4786	0.0001	0.0001	0.0001	0.6889

Table A.27: Coefficients, p-values and R^2 values for
OBE/MOD/Balanced Shop/High Utilization
Iteration #6

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.0503	0.1002	1.2072	0.0001	0.0001	0.0001	0.9874
2	0.9638	0.3545	1.0016	0.0001	0.0001	0.0001	0.9123
3	0.9007	0.3759	1.0574	0.0001	0.0001	0.0001	0.8379
4	0.8076	0.4194	1.1169	0.0001	0.0001	0.0001	0.7735
5	0.7511	0.4482	1.0418	0.0001	0.0001	0.0001	0.7315

Table A.28: Coefficients, p-values and R^2 values for
OBE/MOD/Balanced Shop/Low Utilization
Iteration #6

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	1.6552	0.1942	1.3624	0.0001	0.0001	0.0001	0.8109
2	0.7412	0.2301	1.4129	0.0001	0.0001	0.0001	0.7661
3	0.4275	0.2675	1.5429	0.0001	0.0001	0.0001	0.6927
4	0.3167	0.2423	1.5265	0.0001	0.0001	0.0001	0.6711
5	0.2780	0.2061	1.4606	0.0001	0.0001	0.0001	0.7006

Table A.29: Coefficients, p-values and R^2 values for OBE/SPT/Unbalanced Shop/High Utilization

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	8.5360	1.0403	3.5994	0.0001	0.0001	0.0001	0.3091
12	9.4840	0.7305	0.6673	0.0001	0.0001	0.0439	0.5615
13	7.4268	0.4803	3.0295	0.0001	0.0630	0.0001	0.2540
14	9.0085	0.2419	0.3551	0.0001	0.1492	0.2847	0.5055
15	7.8913	0.3335	0.0785	0.0001	0.0167	0.7648	0.5628
21	6.5076	0.3595	0.8503	0.0001	0.0009	0.0003	0.4498
22	4.1614	0.1511	3.6140	0.0001	0.1904	0.0001	0.3084
23	4.2502	0.1556	1.6159	0.0001	0.0100	0.0001	0.5350
24	4.4217	0.5001	1.6714	0.0001	0.0001	0.0001	0.4421
25	4.3014	0.1202	2.2077	0.0001	0.1430	0.0001	0.4698
31	5.4000	0.1850	1.0866	0.0001	0.0014	0.0001	0.4969
32	3.3698	0.1968	2.0792	0.0001	0.0001	0.0001	0.5204
33	3.0167	0.2141	1.6457	0.0001	0.0001	0.0001	0.5283
34	3.1302	0.2462	1.7490	0.0001	0.0001	0.0001	0.4666
35	1.9055	0.1814	2.3993	0.0001	0.0001	0.0001	0.4872
41	2.7458	0.1984	1.5617	0.0001	0.0001	0.0001	0.6246
42	1.5744	0.2784	1.7488	0.0001	0.0001	0.0001	0.5885
43	2.0970	0.2870	1.7348	0.0001	0.0001	0.0001	0.5136
44	2.2525	0.2053	1.7409	0.0001	0.0001	0.0001	0.5137
45	1.2467	0.1962	2.1559	0.0001	0.0001	0.0001	0.4828
51	3.0576	0.1986	1.2195	0.0001	0.0001	0.0001	0.6847
52	1.3921	0.2139	1.5639	0.0001	0.0001	0.0001	0.6325
53	1.3415	0.2062	1.8030	0.0001	0.0001	0.0001	0.6009
54	0.4371	0.1855	1.9412	0.0001	0.0001	0.0001	0.4959
55	1.1542	0.1574	1.8212	0.0001	0.0001	0.0001	0.5353

Table A.30: Coefficients, p-values and R^2 values for OBE/SPT/Unbalanced Shop/Low Utilization

$$PF_{ji}^k = c_{1j}^k X_{1ji}^k + c_{2j}^k X_{2ji}^k + c_{3j}^k X_{3ji}^k$$

jk	c_{1j}^k	c_{2j}^k	c_{3j}^k	p_{1j}^k	p_{2j}^k	p_{3j}^k	R^2
11	2.5107	0.3753	1.4272	0.0001	0.0001	0.0001	0.6859
12	1.9435	0.3653	1.6969	0.0001	0.0001	0.0001	0.6506
13	1.7087	0.3068	1.8080	0.0001	0.0001	0.0001	0.6128
14	1.3461	0.3440	1.8280	0.0001	0.0001	0.0001	0.5944
15	1.5751	0.3206	1.7781	0.0001	0.0001	0.0001	0.5644
21	2.4046	0.2489	1.3816	0.0001	0.0001	0.0001	0.7216
22	1.9079	0.2808	1.5459	0.0001	0.0001	0.0001	0.5889
23	1.3199	0.3264	1.4836	0.0001	0.0001	0.0001	0.6752
24	1.0658	0.2971	1.7209	0.0001	0.0001	0.0001	0.6309
25	0.8738	0.2935	1.7081	0.0001	0.0001	0.0001	0.5855
31	2.1853	0.1854	1.3402	0.0001	0.0001	0.0001	0.7706
32	1.1071	0.3446	1.4972	0.0001	0.0001	0.0001	0.6175
33	1.6129	0.3028	1.4590	0.0001	0.0001	0.0001	0.6273
34	0.7596	0.2839	1.5204	0.0001	0.0001	0.0001	0.6600
35	0.3134	0.2597	1.6534	0.0001	0.0001	0.0001	0.6320
41	1.9962	0.1807	1.2655	0.0001	0.0001	0.0001	0.7664
42	1.1958	0.3011	1.2876	0.0001	0.0001	0.0001	0.7128
43	0.9057	0.3094	1.3116	0.0001	0.0001	0.0001	0.6765
44	0.3726	0.2567	1.3851	0.0001	0.0001	0.0001	0.6499
45	0.2551	0.2423	1.5018	0.0001	0.0001	0.0001	0.6677
51	1.6697	0.1222	1.2490	0.0001	0.0001	0.0001	0.7973
52	0.8536	0.2474	1.2230	0.0001	0.0001	0.0001	0.7216
53	0.6346	0.2600	1.2523	0.0001	0.0001	0.0001	0.7145
54	0.3182	0.2128	1.3316	0.0001	0.0001	0.0001	0.6782
55	0.5595	0.1821	1.3864	0.0001	0.0001	0.0001	0.6783

Table A.31: Coefficients, p-values and R^2 values for OBE/SPT/Balanced Shop/High Utilization

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	4.5120	0.2092	1.3814	0.0001	0.0001	0.0001	0.5729
2	3.8511	0.2515	1.3685	0.0001	0.0001	0.0001	0.6387
3	1.9691	0.2708	2.4991	0.0001	0.0001	0.0001	0.3385
4	2.0363	0.1750	2.1381	0.0001	0.0001	0.0001	0.5303
5	3.8955	0.1090	1.7933	0.0001	0.0535	0.0001	0.4901

Table A.32: Coefficients, p-values and R^2 values for OBE/SPT/Balanced Shop/Low Utilization

$PF_i^k = c_1^k X_{1i}^k + c_2^k X_{2i}^k + c_3^k X_{3i}^k$							
k	c_1^k	c_2^k	c_3^k	p_1^k	p_2^k	p_3^k	R^2
1	2.0438	0.1670	1.4388	0.0001	0.0001	0.0001	0.7143
2	1.3270	0.2897	1.4161	0.0001	0.0001	0.0001	0.7103
3	1.2359	0.2556	1.5271	0.0001	0.0001	0.0001	0.6343
4	0.6023	0.3012	1.4593	0.0001	0.0001	0.0001	0.6665
5	0.2847	0.2966	1.5847	0.0001	0.0001	0.0001	0.6314

Table A.33: Coefficients, p-values and R^2 values for COFS/Unbalanced Shop/High Utilization

$\sqrt[4]{F_i} = k_1T_i + k_2Q_i + k_3N_i + k_4P_i$									
	k_1	k_2	k_3	k_4	p_1	p_2	p_3	p_4	R^2
FCFS	0.5370	0.0134	0.0477	0.1410	0.0001	0.0001	0.0001	0.0001	0.9764
MOD Iter #1	0.4739	0.0101	−0.0073	0.0798	0.0001	0.0001	0.2499	0.0001	0.9620
MOD Iter #2	0.4629	0.0110	0.0138	0.0775	0.0001	0.0001	0.0057	0.0001	0.9763
MOD Iter #3	0.4753	0.0118	0.0036	0.0758	0.0001	0.0001	0.4570	0.0001	0.9775
MOD Iter #4	0.4742	0.0110	0.0028	0.0767	0.0001	0.0001	0.5596	0.0001	0.9766
MOD Iter #5	0.4809	0.0100	0.0066	0.747	0.0001	0.0001	0.1774	0.0001	0.9771
MOD Iter #6	0.4631	0.0111	0.0209	0.0725	0.0001	0.0001	0.0001	0.0001	0.9774
SPT	0.4501	0.0042	0.0261	0.0766	0.0001	0.0022	0.0004	0.0001	0.9437

Table A.34: Coefficients, p-values and R^2 values for COFS/Balanced Shop/High Utilization

$\sqrt[4]{F_i} = k_1T_i + k_2Q_i + k_3N_i + k_4P_i$									
	k_1	k_2	k_3	k_4	p_1	p_2	p_3	p_4	R^2
FCFS	0.5793	0.0108	0.0267	0.0172	0.0001	0.0001	0.0001	0.0001	0.9782
MOD Iter #1	0.5044	0.0059	−0.0046	0.0726	0.0001	0.0001	0.4394	0.0001	0.9671
MOD Iter #2	0.5139	0.0080	−0.0028	0.0696	0.0001	0.0001	0.5801	0.0001	0.9750
MOD Iter #3	0.3956	0.0158	0.1127	0.0560	0.0001	0.0001	0.0001	0.0001	0.9700
MOD Iter #4	0.4765	0.0121	0.0404	0.0617	0.0001	0.0001	0.0001	0.0001	0.9774
MOD Iter #5	0.5038	0.0106	0.0161	0.0627	0.0001	0.0001	0.0009	0.0001	0.9776
MOD Iter #6	0.5151	0.0103	0.0075	0.0617	0.0001	0.0001	0.1101	0.0001	0.9784
SPT	0.4841	0.0079	0.0122	0.0678	0.0001	0.0001	0.0834	0.0001	0.9487

Table A.35: Coefficients, p-values and R^2 values for COFS/Unbalanced Shop/Low Utilization

$$\sqrt[4]{F_i} = k_1T_i + k_2Q_i + k_3N_i + k_4P_i$$

	k_1	k_2	k_3	k_4	p_1	p_2	p_3	p_4	R^2
FCFS	0.5530	0.0213	0.0460	0.0282	0.0001	0.0001	0.0001	0.0001	0.9595
MOD Iter #1	0.5156	0.0105	0.0289	0.0568	0.0001	0.0001	0.0001	0.0001	0.9561
MOD Iter #2	0.5538	0.0101	0.0132	0.0529	0.0001	0.0001	0.0222	0.0001	0.9610
MOD Iter #3	0.5465	0.0104	0.0184	0.0528	0.0001	0.0001	0.0013	0.0001	0.9624
MOD Iter #4	0.5435	0.0098	0.0218	0.0526	0.0001	0.0001	0.0001	0.0001	0.9632
MOD Iter #5	0.5367	0.0105	0.0249	0.0527	0.0001	0.0001	0.0001	0.0001	0.9630
MOD Iter #6	0.5430	0.0096	0.0208	0.0534	0.0001	0.0001	0.0001	0.0001	0.9629
SPT	0.5244	0.0058	0.0256	0.0543	0.0001	0.0226	0.0001	0.0001	0.9479

Table A.36: Coefficients, p-values and R^2 values for COFS/Balanced Shop/Low Utilization

$$\sqrt[4]{F_i} = k_1T_i + k_2Q_i + k_3N_i + k_4P_i$$

	k_1	k_2	k_3	k_4	p_1	p_2	p_3	p_4	R^2
FCFS	0.5761	0.0183	0.0297	0.0305	0.0001	0.0001	0.0001	0.0001	0.9585
MOD Iter #1	0.5421	0.0070	0.0186	0.0554	0.0001	0.0015	0.0025	0.0001	0.9567
MOD Iter #2	0.5619	0.0080	0.0195	0.0487	0.0001	0.0001	0.0007	0.0001	0.9622
MOD Iter #3	0.5685	0.0105	0.0141	0.0278	0.0001	0.0001	0.0132	0.0001	0.9620
MOD Iter #4	0.5656	0.0098	0.0158	0.0484	0.0001	0.0001	0.0057	0.0001	0.9616
MOD Iter #5	0.5677	0.0092	0.0155	0.0478	0.0001	0.0001	0.0065	0.0001	0.9620
MOD Iter #6	0.5687	0.0091	0.0164	0.0470	0.0001	0.0001	0.0041	0.0001	0.9617
SPT	0.5718	0.0066	0.0006	0.0528	0.0001	0.0143	0.9194	0.0001	0.9489

Table A.37: Coefficients, p-values and R^2 values for OFS/Unbalanced Shop/High Utilization

$$\sqrt[4]{F_i} = k_1T_i + k_2N_i + k_3P_i$$

	k_1	k_2	k_3	p_1	p_2	p_3	R^2
FCFS	0.5805	0.0855	0.0153	0.0001	0.0001	0.0001	0.9707
MOD Iter #1	0.4842	0.0115	0.0801	0.0001	0.0635	0.0001	0.9613
MOD Iter #2	0.4899	0.0130	0.0800	0.0001	0.0111	0.0001	0.9728
MOD Iter #3	0.4849	0.0174	0.0799	0.0001	0.0003	0.0001	0.9752
MOD Iter #4	0.4910	0.0120	0.0795	0.0001	0.0173	0.0001	0.9744
MOD Iter #5	0.4835	0.0156	0.0813	0.0001	0.0021	0.0001	0.9729
MOD Iter #6	0.4875	0.0140	0.0805	0.0001	0.0049	0.0001	0.9742
SPT	0.4522	0.03339	0.0766	0.0001	0.0001	0.0001	0.9436

Table A.38: Coefficients, p-values and R^2 values for OFS/Balanced Shop/High Utilization

$$\sqrt[4]{F_i} = k_1T_i + k_2N_i + k_3P_i$$

	k_1	k_2	k_3	p_1	p_2	p_3	R^2
FCFS	0.6085	0.0478	0.0174	0.0001	0.0001	0.0001	0.9762
MOD Iter #1	0.5102	0.0042	0.0727	0.0001	0.4577	0.0001	0.9670
MOD Iter #2	0.5293	0.0014	0.0699	0.0001	0.7664	0.0001	0.9754
MOD Iter #3	0.5310	0.0035	0.0679	0.0001	0.4691	0.0001	0.9765
MOD Iter #4	0.5376	0.0042	0.0697	0.0001	0.3855	0.0001	0.9757
MOD Iter #5	0.5344	0.0037	0.0660	0.0001	0.4368	0.0001	0.9766
MOD Iter #6	0.5329	0.0048	0.0667	0.0001	0.3150	0.0001	0.0001
SPT	0.4882	0.0238	0.0679	0.0001	0.0004	0.0001	0.9485

Table A.39: Coefficients, p-values and R^2 values for OFS/Unbalanced Shop/Low Utilization

$\sqrt[4]{F_i} = k_1T_i + k_2N_i + k_3P_i$							
	k_1	k_2	k_3	p_1	p_2	p_3	R^2
FCFS	0.5842	0.0487	0.0288	0.0001	0.0001	0.0001	0.9578
MOD Iter #1	0.5231	0.0325	0.0570	0.0001	0.0001	0.0001	0.9559
MOD Iter #2	0.5592	0.0245	0.0503	0.0001	0.0001	0.0001	0.9619
MOD Iter #3	0.5531	0.0302	0.0496	0.0001	0.0001	0.0001	0.9617
MOD Iter #4	0.5535	0.0284	0.0500	0.0001	0.0001	0.0001	0.9625
MOD Iter #5	0.5595	0.0243	0.0501	0.0001	0.0001	0.0001	0.9621
MOD Iter #6	0.5642	0.0233	0.0493	0.0001	0.0001	0.0001	0.9622
SPT	0.5271	0.0280	0.0544	0.0001	0.0001	0.0001	0.9478

Table A.40: Coefficients, p-values and R^2 values for OFS/Balanced Shop/Low Utilization

$\sqrt[4]{F_i} = k_1T_i + k_2N_i + k_3P_i$							
	k_1	k_2	k_3	p_1	p_2	p_3	R^2
FCFS	0.5988	0.0329	0.0308	0.0001	0.0001	0.0001	0.9575
MOD Iter #1	0.5463	0.0214	0.0554	0.0001	0.0005	0.0001	0.9567
MOD Iter #2	0.5592	0.0245	0.503	0.0001	0.0001	0.0001	0.9619
MOD Iter #3	0.5655	0.0226	0.0486	0.0001	0.0001	0.0001	0.9616
MOD Iter #4	0.5725	0.0163	0.0495	0.0001	0.0004	0.0001	0.9619
MOD Iter #5	0.5627	0.0238	0.0491	0.0001	0.0001	0.0001	0.9619
MOD Iter #6	0.5805	0.0124	0.0490	0.0001	0.0001	0.0001	0.9618
SPT	0.5747	0.0033	0.0528	0.0001	0.6097	0.0001	0.9488

Table A.41: Coefficients, p-values and R^2 values for JIQ and TWK Unbalanced Shop/High Utilization

	$F_i = k_1 P_i + k_2 Q_i$					$F_i = k P_i$		
	k_1	k_2	p_1	p_2	R^2	k	p	R^2
FCFS	1.4364	2.4441	0.0001	0.0001	0.9542	7.0352	0.0001	0.6134
MOD Iter #1	2.5008	1.9776	0.0001	0.0001	0.5978	4.7343	0.0001	0.4566
MOD Iter #2	2.5714	1.9677	0.0001	0.0001	0.6007	4.5024	0.0001	0.5952
MOD Iter #3	2.7671	1.6883	0.0001	0.0001	0.5649	4.6637	0.0001	0.4301
MOD Iter #4	3.3689	1.3950	0.0001	0.0001	0.4920	4.6290	0.0001	0.5241
MOD Iter #5	3.0567	1.4922	0.0001	0.0001	0.5802	4.6123	0.0001	0.4886
MOD Iter #6	3.3106	1.3581	0.0001	0.0001	0.4860	4.5764	0.0001	0.5406
SPT	4.2008	−0.0834	0.0001	0.3764	0.4047	4.0583	0.0001	0.2769

Table A.42: Coefficients, p-values and R^2 values for JIQ and TWK Balanced Shop/High Utilization

	$F_i = k_1 P_i + k_2 Q_i$					$F_i = k P_i$		
	k_1	k_2	p_1	p_2	R^2	k	p	R^2
FCFS	1.4840	2.3370	0.0001	0.0001	0.9378	5.3414	0.0001	0.6444
MOD Iter #1	2.0142	1.9154	0.0001	0.0001	0.8063	3.9661	0.0001	0.7798
MOD Iter #2	2.0678	1.8949	0.0001	0.0001	0.8441	3.7906	0.0001	0.5958
MOD Iter #3	2.2456	1.6839	0.0001	0.0001	0.7944	3.7629	0.0001	0.7037
MOD Iter #4	2.3082	1.6261	0.0001	0.0001	0.8006	3.6635	0.0001	0.7194
MOD Iter #5	2.4144	1.5923	0.0001	0.0001	0.7794	3.7272	0.0001	0.7174
MOD Iter #6	2.4688	1.5825	0.0001	0.0001	0.8862	3.8155	0.0001	0.6675
SPT	2.9566	0.7194	0.0001	0.0001	0.4879	3.4514	0.0001	0.4904

Table A.43: Coefficients, p-values and R^2 values for JIQ and TWK Unbalanced Shop/Low Utilization

	$F_i = k_1P_i + k_2Q_i$					$F_i = kP_i$		
	k_1	k_2	p_1	p_2	R^2	k	p	R^2
FCFS	1.3804	2.6316	0.0001	0.0001	0.9027	2.6524	0.0001	0.6954
MOD Iter #1	1.7010	2.0328	0.0001	0.0001	0.8590	2.3461	0.0001	0.8226
MOD Iter #2	1.6377	1.8826	0.0001	0.0001	0.8690	2.2374	0.0001	0.7522
MOD Iter #3	1.6878	1.7507	0.0001	0.0001	0.7513	2.2666	0.0001	0.6908
MOD Iter #4	1.7021	0.1.7252	0.0001	0.0001	0.8171	2.2468	0.0001	0.7443
MOD Iter #5	1.7153	1.7042	0.0001	0.0001	0.8149	2.2602	0.0001	0.6946
MOD Iter #6	1.7247	1.6724	0.0001	0.0001	0.8147	2.2733	0.0001	0.6831
SPT	1.7846	1.2545	0.0001	0.0001	0.7283	2.1218	0.0001	0.7068

Table A.44: Coefficients, p-values and R^2 values for JIQ and TWK Balanced Shop/Low Utilization

	$F_i = k_1P_i + k_2Q_i$					$F_i = kP_i$		
	k_1	k_2	p_1	p_2	R^2	k	p	R^2
FCFS	1.3836	2.4872	0.0001	0.0001	0.8882	2.4248	0.0001	0.7162
MOD Iter #1	1.6529	1.8902	0.0001	0.0001	0.8659	2.2528	0.0001	0.8331
MOD Iter #2	1.5812	1.8014	0.0001	0.0001	0.8803	2.0812	0.0001	0.8334
MOD Iter #3	1.5707	1.7935	0.0001	0.0001	0.8789	2.0603	0.0001	0.8387
MOD Iter #4	1.5952	1.7570	0.0001	0.0001	0.8704	2.0541	0.0001	0.8376
MOD Iter #5	1.5794	1.7560	0.0001	0.0001	0.8864	2.0484	0.0001	0.8380
MOD Iter #6	1.6057	1.7325	0.0001	0.0001	0.8685	2.0527	0.0001	0.8384
SPT	1.7615	1.1988	0.0001	0.0001	0.7803	2.0615	0.0001	0.7601

Appendix B

Simulation Model

B.1 Model Frame

```
BEGIN,no;
          CREATE: EX(7,1), NoBat: MARK(TimeIn);
          ASSIGN: NumOp = DISCRETE(0.2,1,0.4,2,0.6,3,0.8,4,1,5,2):
                  NumAssMac = 0;
ReAssign  BRANCH,1:
                IF, NumAssMac <> NumOp, AssignJob:
                ELSE, GoOn;
AssignJob ASSIGN: A(NumAssMac+1) = DISCRETE(0.2,1,0.4,2,0.6,3,
                                       0.8,4,1,5,3);
          BRANCH,1:
                IF, (A(1) == A(NumAssMac+1)) .AND.
                    ((NumAssMac+1) <> 1), AssignJob:
                IF, (A(2) == A(NumAssMac+1)) .AND.
                    ((NumAssMac+1) <> 2), AssignJob:
                IF, (A(3) == A(NumAssMac+1)) .AND.
                    ((NumAssMac+1) <> 3), AssignJob:
                IF, (A(4) == A(NumAssMac+1)) .AND.
                    ((NumAssMac+1) <> 4), AssignJob:
                IF, (A(5) == A(NumAssMac+1)) .AND.
                    ((NumAssMac+1) <> 5), AssignJob:
                ELSE, NoProb;
NoProb    ASSIGN: NumAssMac = NumAssMac +1:
                  A(5+NumAssMac) = EX(A(NumAssMac),4):
                  TotalProcT = TotalProcT + A(5+NumAssMac):
                  A(35+NumAssMac) = TotalProcT: NEXT(ReAssign);


GoOn      ASSIGN: SENT1 = 1;
To1       ASSIGN: A(40+SENT1)=TNOW+(p(6,1)*A(35+SENT1));
          BRANCH,1:
                IF, NQ(A(SENT1)) == 0, IncSent1:
                ELSE, So1;
So1       ASSIGN: Cnt = 1:
                  M = A(SENT1);
          EVENT:1;
```

```
So2        BRANCH,1:
                 IF, AQUE(A(SENT1),Cnt,19)<A(40+SENT1), CollectIt:
                 ELSE, IncCnt;
CollectIt ASSIGN: ObsVals(SENT1,1) = ObsVals(SENT1,1)+
                                 AQUE(A(SENT1),Cnt,16);
IncCnt     ASSIGN: Cnt = Cnt + 1;
           BRANCH,1:
                 IF, (NQ(A(SENT1))+1) == Cnt, IncSent1:
                 ELSE, So2;
IncSent1   ASSIGN: SENT1 = SENT1 +1;
           BRANCH,1:
                 IF, (A(SENT1) == 0) .OR. (SENT1 == 6), To2:
                 ELSE, To1;

; Obtain the X2 values for each operation
To2        ASSIGN: OpNo = 1:
                   LookQNo = 1:
                   Sum = 0;
To6        BRANCH,1:
                 IF, LookQNo == 6, To3:
                 IF, LookQNo == A(OpNo), To4:
                 ELSE, To5;
To4        ASSIGN: LookQNo = LookQNo + 1: NEXT(To6);
To5        ASSIGN: SENT2 = 2;
To14       ASSIGN: BeJ = 1:
                   ToWhichM = A(OpNo);
To11       SEARCH, LookQNo, BeJ, NQ:
               ((A(SENT2) == ToWhichM) .AND. (OpInd < SENT2));
           BRANCH,1:
                 IF, J .GT. 0 , To7:
                 ELSE, To10;
To7        ASSIGN: ModVal = TNOW +
                 (((AQUE(LookQNo,J,14)-TNOW)/
                   (AQUE(LookQNo,J,35+AQUE(LookQNo,J,12)) -
                    AQUE(LookQNo,J,34+AQUE(LookQNo,J,13)))) *
                   (AQUE(LookQNo,J,35+SENT2) -
                    AQUE(LookQNo,J,34+AQUE(LookQNo,J,13))));
           ASSIGN: ModVal = MX(ModVal,
                 TNOW+(AQUE(LookQNo,J,35+SENT2)-
                  AQUE(LookQNo,J,34+AQUE(LookQNo,J,13))));
           BRANCH,1:
                 IF, ModVal < A(40+OpNo), AddIt:
                 ELSE,Br;
AddIt      ASSIGN: Sum = Sum + AQUE(LookQNo,J,5+SENT2);
Br         BRANCH,1:
                 IF, J < NQ(LookQNo), To9:
                 ELSE, To10;
To9        ASSIGN: BeJ = J + 1: NEXT(To11);
To10       ASSIGN:SENT2 = SENT2 + 1;
           BRANCH,1:
                 IF, SENT2 > 5, To12:
                 ELSE, To14;
To12       BRANCH,1:
                 IF, NR(LookQNo) == 1, bsy:
                 ELSE, IncQNo;
bsy        BRANCH,1:
                 IF, NextMacOp(LookQNo,1) == A(OpNo) .OR.
                     NextMacOp(LookQNo,2) == A(OpNo) .OR.
                     NextMacOp(LookQNo,3) == A(OpNo) .OR.
                     NextMacOp(LookQNo,4) == A(OpNo), AS :
                 ELSE, IncQNo;
AS         ASSIGN: Sum = Sum + NextMacOpT(LookQNo,1);

IncQNo     ASSIGN: LookQNo = LookQNo + 1: NEXT(To6);
```

```
To3         ASSIGN: ObsVals(OpNo,2) = Sum:
                    OpNo = OpNo + 1;
            BRANCH,1:
                  IF, ((OpNo ==6) .OR. (A(OpNo) == 0)), GetDueDat:
                  ELSE, To15;
To15        ASSIGN: LookQNo = 1:
                    Sum = 0: NEXT(To6);

To16        ASSIGN: CurrProcT = A(6):
                    OpInd =1:
                    EntTime = TNOW;
            ROUTE:0, A(1);
            STATION,1-5;
            BRANCH,1:
                  IF, NR(M) == 0, SzIt:
                  ELSE, DetQ;
DetQ        QUEUE, M:DETACH;
SzIt        QUEUE, M+5;
            SEIZE: Machine(M);
            BRANCH,1:
                  IF, (NumOp - OpInd) == 0 , setn0:
                  IF, (NumOp - OpInd) == 1 , setn1:
                  IF, (NumOp - OpInd) == 2 , setn2:
                  IF, (NumOp - OpInd) == 3 , setn3:
                  IF, (NumOp - OpInd) == 4 , setn4:
                  ELSE, wrerr;
setn0       ASSIGN: NextMacOp(M,1) = 0:
                    NextMacOp(M,2) = 0:
                    NextMacOp(M,3) = 0:
                    NextMacOp(M,4) = 0:NEXT(ToDly);
setn1       ASSIGN: NextMacOp(M,1) = A(OpInd+1):
                    NextMacOpT(M,1)= A(OpInd+6):
                    NextMacOp(M,2) = 0:
                    NextMacOp(M,3) = 0:
                    NextMacOp(M,4) = 0:NEXT(ToDly);
setn2       ASSIGN: NextMacOp(M,1) = A(OpInd+1):
                    NextMacOpT(M,1)= A(OpInd+6):
                    NextMacOp(M,2) = A(OpInd+2):
                    NextMacOpT(M,2)= A(OpInd+7):
                    NextMacOp(M,3) = 0:
                    NextMacOp(M,4) = 0:NEXT(ToDly);
setn3       ASSIGN: NextMacOp(M,1) = A(OpInd+1):
                    NextMacOpT(M,1)= A(OpInd+6):
                    NextMacOp(M,2) = A(OpInd+2):
                    NextMacOpT(M,2)= A(OpInd+7):
                    NextMacOp(M,3) = A(OpInd+3):
                    NextMacOpT(M,3)= A(OpInd+8):
                    NextMacOp(M,4) = 0:NEXT(ToDly);
setn4       ASSIGN: NextMacOp(M,1) = A(OpInd+1):
                    NextMacOpT(M,1)= A(OpInd+6):
                    NextMacOp(M,2) = A(OpInd+2):
                    NextMacOpT(M,2)= A(OpInd+7):
                    NextMacOp(M,3) = A(OpInd+3):
                    NextMacOpT(M,3)= A(OpInd+8):
                    NextMacOp(M,4) = A(OpInd+4):
                    NextMacOpT(M,4)= A(OpInd+9):NEXT(ToDly);
wrerr       WRITE:tnow;
            ASSIGN: NoBat = 1;
ToDly       ASSIGN: QuTime(M) = TNOW;
            DELAY: CurrProcT;
            ASSIGN: BTI(M) = BTI(M) + TNOW - QuTime(M);
            ASSIGN: NextMacOp(M,1) = 0:
                    NextMacOp(M,2) = 0:
                    NextMacOp(M,3) = 0:
```

```
                NextMacOp(M,4) = 0;
          BRANCH,1:
                IF, NQ(M) == 0, RelIt:
                ELSE, HowMany;
HowMany   BRANCH,1:
                IF, NQ(M) == 1, ToOne:
                ELSE, DupIt;
ToOne     REMOVE:1, M, SzIt: NEXT(RelIt);
DupIt     DUPLICATE:1, RelIt: NEXT(AssPrios);
RelIt     RELEASE: Machine(M);
          ASSIGN: ObsVals(OpInd,3) = TNOW - EntTime;
          ASSIGN: OpInd = OpInd + 1:
                CurrProcT = A(5+OpInd);
          BRANCH,1:
                IF, OpInd > NumOp, Exit:
                ELSE, SetIt;
Setit     ASSIGN: EntTime = TNOW ;
          ROUTE:0, A(OpInd);

;Assign Priorities to Entities in the Detached Queue
AssPrios  EVENT:1;
          SEARCH,M,1,NQ: MIN(Priority);
          REMOVE:J,M,SzIt:DISPOSE;

exit      BRANCH,1:
                IF, TNOW < 20000, senit:
                ELSE, Talliti;
Talliti          TALLY: 1, INTERVAL(TimeIn);
          TALLY: 2, (TNOW -DueDate);
          TALLY: 3, MX(0, (TNOW-DueDate));
          TALLY: 4, ((TNOW-DueDate)*(TNOW-DueDate));
          TALLY: 5, ABS(TNOW-DueDate);
          BRANCH,1:
                IF, (TNOW-DueDate) < 0, Abso:
                ELSE, SqrL;
Abso      ASSIGN: SQLVal = ABS(TNOW-DueDate): NEXT(Tallit);
SqrL      ASSIGN: SQLVal = ((TNOW-DueDate)*(TNOW-DueDate));
Tallit    TALLY: 6, SQLVal;
          BRANCH,1:
                IF, (TNOW-DueDate) > 0,  PcrT:
                ELSE, AlsoCnt;
PcrT      COUNT:1;
AlsoCnt   COUNT:2;
          COUNT:SelectedJobs;
senit     COUNT:AllJobs:DISPOSE;

GetDueDat ASSIGN: OpInd = 0:
                DueDate = TNOW;
OtherOp   ASSIGN: OpInd = OpInd + 1;
          BRANCH,1:
                IF, (A(OpInd)== 0) .OR. (OpInd == 6), To16:
                ELSE, DetMac;
DetMac    BRANCH,1:
                IF, A(OpInd) == 1, SelM1:
                IF, A(OpInd) == 2, SelM2:
                IF, A(OpInd) == 3, SelM3:
                IF, A(OpInd) == 4, SelM4:
                IF, A(OpInd) == 5, SelM5;

SelM1     BRANCH,1:
                IF, OpInd == 1, ToE11:
                IF, OpInd == 2, ToE12:
                IF, OpInd == 3, ToE13:
                IF, OpInd == 4, ToE14:
```

```
                IF, OpInd == 5, ToE15;
SelM2      BRANCH,1:
                IF, OpInd == 1, ToE21:
                IF, OpInd == 2, ToE22:
                IF, OpInd == 3, ToE23:
                IF, OpInd == 4, ToE24:
                IF, OpInd == 5, ToE25;
SelM3      BRANCH,1:
                IF, OpInd == 1, ToE31:
                IF, OpInd == 2, ToE32:
                IF, OpInd == 3, ToE33:
                IF, OpInd == 4, ToE34:
                IF, OpInd == 5, ToE35;
SelM4      BRANCH,1:
                IF, OpInd == 1, ToE41:
                IF, OpInd == 2, ToE42:
                IF, OpInd == 3, ToE43:
                IF, OpInd == 4, ToE44:
                IF, OpInd == 5, ToE45;
SelM5     BRANCH,1:
                IF, OpInd == 1, ToE51:
                IF, OpInd == 2, ToE52:
                IF, OpInd == 3, ToE53:
                IF, OpInd == 4, ToE54:
                IF, OpInd == 5, ToE55;

ToE11     ASSIGN: DueDate = DueDate  +(P(11,1)*ObsVals(OpInd,1))
                                   + (P(11,2)*ObsVals(OpInd,2))
                                   + (P(11,3)*A(OpInd+5)): NEXT(OtherOp);
ToE12     ASSIGN: DueDate = DueDate  +(P(12,1)*ObsVals(OpInd,1))
                                   + (P(12,2)*ObsVals(OpInd,2))
                                   + (P(12,3)*A(OpInd+5)): NEXT(OtherOp);
ToE13     ASSIGN: DueDate = DueDate  +(P(13,1)*ObsVals(OpInd,1))
                                   + (P(13,2)*ObsVals(OpInd,2))
                                   + (P(13,3)*A(OpInd+5)): NEXT(OtherOp);
ToE14     ASSIGN: DueDate = DueDate  +(P(14,1)*ObsVals(OpInd,1))
                                   + (P(14,2)*ObsVals(OpInd,2))
                                   + (P(14,3)*A(OpInd+5)): NEXT(OtherOp);
ToE15     ASSIGN: DueDate = DueDate  +(P(15,1)*ObsVals(OpInd,1))
                                   + (P(15,2)*ObsVals(OpInd,2))
                                   + (P(15,3)*A(OpInd+5)): NEXT(OtherOp);


ToE21     ASSIGN: DueDate = DueDate  +(P(16,1)*ObsVals(OpInd,1))
                                   + (P(16,2)*ObsVals(OpInd,2))
                                   + (P(16,3)*A(OpInd+5)): NEXT(OtherOp);
ToE22     ASSIGN: DueDate = DueDate  +(P(17,1)*ObsVals(OpInd,1))
                                   + (P(17,2)*ObsVals(OpInd,2))
                                   + (P(17,3)*A(OpInd+5)): NEXT(OtherOp);
ToE23     ASSIGN: DueDate = DueDate  +(P(18,1)*ObsVals(OpInd,1))
                                   + (P(18,2)*ObsVals(OpInd,2))
                                   + (P(18,2)*A(OpInd+5)): NEXT(OtherOp);
ToE24     ASSIGN: DueDate = DueDate  +(P(19,1)*ObsVals(OpInd,1))
                                   + (P(19,2)*ObsVals(OpInd,2))
                                   + (P(19,3)*A(OpInd+5)): NEXT(OtherOp);
ToE25     ASSIGN: DueDate = DueDate  +(P(20,1)*ObsVals(OpInd,1))
                                   + (P(20,2)*ObsVals(OpInd,2))
                                   + (P(20,3)*A(OpInd+5)): NEXT(OtherOp);


ToE31     ASSIGN: DueDate = DueDate  +(P(21,1)*ObsVals(OpInd,1))
                                   + (P(21,2)*ObsVals(OpInd,2))
                                   + (P(21,3)*A(OpInd+5)): NEXT(OtherOp);
```

```
ToE32     ASSIGN: DueDate = DueDate  +(P(22,1)*ObsVals(OpInd,1))
                             + (P(22,2)*ObsVals(OpInd,2))
                             + (P(22,3)*A(OpInd+5)): NEXT(OtherOp);
ToE33     ASSIGN: DueDate = DueDate  +(P(23,1)*ObsVals(OpInd,1))
                             + (P(23,2)*ObsVals(OpInd,2))
                             + (P(23,3)*A(OpInd+5)): NEXT(OtherOp);
ToE34     ASSIGN: DueDate = DueDate  +(P(24,1)*ObsVals(OpInd,1))
                             + (P(24,2)*ObsVals(OpInd,2))
                             + (P(24,3)*A(OpInd+5)): NEXT(OtherOp);
ToE35     ASSIGN: DueDate = DueDate  +(P(25,1)*ObsVals(OpInd,1))
                             + (P(25,2)*ObsVals(OpInd,2))
                             + (P(25,3)*A(OpInd+5)): NEXT(OtherOp);


ToE41     ASSIGN: DueDate = DueDate  +(P(26,1)*ObsVals(OpInd,1))
                             + (P(26,2)*ObsVals(OpInd,2))
                             + (P(26,3)*A(OpInd+5)): NEXT(OtherOp);
ToE42     ASSIGN: DueDate = DueDate  +(P(27,1)*ObsVals(OpInd,1))
                             + (P(27,2)*ObsVals(OpInd,2))
                             + (P(27,3)*A(OpInd+5)): NEXT(OtherOp);
ToE43     ASSIGN: DueDate = DueDate  +(P(28,1)*ObsVals(OpInd,1))
                             + (P(28,2)*ObsVals(OpInd,2))
                             + (P(28,3)*A(OpInd+5)): NEXT(OtherOp);
ToE44     ASSIGN: DueDate = DueDate  +(P(29,1)*ObsVals(OpInd,1))
                             + (P(29,2)*ObsVals(OpInd,2))
                             + (P(29,3)*A(OpInd+5)): NEXT(OtherOp);
ToE45     ASSIGN: DueDate = DueDate  +(P(30,1)*ObsVals(OpInd,1))
                             + (P(30,2)*ObsVals(OpInd,2))
                             + (P(30,3)*A(OpInd+5)): NEXT(OtherOp);


ToE51     ASSIGN: DueDate = DueDate  +(P(31,1)*ObsVals(OpInd,1))
                             + (P(31,2)*ObsVals(OpInd,2))
                             + (P(31,3)*A(OpInd+5)): NEXT(OtherOp);
ToE52     ASSIGN: DueDate = DueDate  +(P(32,1)*ObsVals(OpInd,1))
                             + (P(32,2)*ObsVals(OpInd,2))
                             + (P(32,3)*A(OpInd+5)): NEXT(OtherOp);
ToE53     ASSIGN: DueDate = DueDate  +(P(33,1)*ObsVals(OpInd,1))
                             + (P(33,2)*ObsVals(OpInd,2))
                             + (P(33,3)*A(OpInd+5)): NEXT(OtherOp);
ToE54     ASSIGN: DueDate = DueDate  +(P(34,1)*ObsVals(OpInd,1))
                             + (P(34,2)*ObsVals(OpInd,2))
                             + (P(34,3)*A(OpInd+5)): NEXT(OtherOp);
ToE55     ASSIGN: DueDate = DueDate  +(P(35,1)*ObsVals(OpInd,1))
                             + (P(35,2)*ObsVals(OpInd,2))
                             + (P(35,3)*A(OpInd+5)): NEXT(OtherOp);

CREATE,5;
           ASSIGN: M = Dwncnt + 1:
                   DwnCnt =  DwnCnt + 1;
           ASSIGN: UpTime(M) = GAMMA(scaleu,shapeu(M),7);
           DELAY: UpTime(M);
test       BRANCH,1:
                 IF, NR(Machine(M)) == 1, test1:
                 ELSE, test2;
test1      BRANCH,1:
                 IF, (BTI(M) + TNOW - QuTime(M))
                    < (UpTime(M) - 0.5), pass1:
                 ELSE, brk;
test2      BRANCH,1:
                 IF, (UpTime(M) - BTI(M)) < 0.5, atla1:
                 ELSE, atla2;
atla1      DELAY:0.5:NEXT(test);
```

```
atla2       DELAY: UpTime(M) - BTI(M) : NEXT(test);
pass1       DELAY: UpTime(M) - (BTI(M)+TNOW -
                   QuTime(M)):NEXT(test);
brk         QUEUE, preque;
            PREEMPT: Machine(M);
            ASSIGN: MachDown(M) = 1;
            DELAY: GAMMA(scaled, shaped(M),8);
regen       ASSIGN: MachDown(M) = 0:
                    UpTime(M) = GAMMA(scaleu, shapeu(M),7):
                    BTI(M) = 0:
                    QuTime(M) = TNOW;
            BRANCH,1:
                  IF, UpTime(M) < 0.5, regen:
                  ELSE, GoRelease;
GoRelease RELEASE: Machine(M);
            DELAY: UpTime(M): NEXT(test);

END;
```

B.2 Experimental Frame

```
BEGIN,no;

      PROJECT, MYES MOD, AComlekci;
      ATTRIBUTES:1-5, MacNum(5):
                 6-10,ProcTim(5):
                 11, TimeIn:
                 12, NumOp:
                 13, OpInd,1:
                 14, DueDate:
                 15,BeJ:
                 16,CurrProcT:
                 17,EntTime:
                 18, TotalProcT:
                 19,Priority:
                 21-35, ObsVals(5,3):
                 36-40, ParTT(5):
                 41-45, ParFA(5);
      VARIABLES: SENT1:
                 SENT2:
                 NumAssMac:
                 SQLVal:
                 DumCnt:
                 ToWhichM:
                 OpNo:
                 LookQNo:
                 Sum:
                 LastRecd(25), -50:
                 Say(25):
                 NextMacOp(5,4):
                 NextMacOpT(5,4):
                 NoBat,9999999:
                 Lag, 50:
                 Cnt:
                 ModVal:
                 QuTime(5):
                 BTI(5):
                 DwnCnt:
                 UpTime(5):
                 scaleu,0.7:
                 scaled,1.4:
                 shapeu(5),385.7143:
                 shaped(5),8.03571:
                 MachDown(5);
      STATIONS:5;
      RESOURCES: Machine(5);

      QUEUES:10:
             11, preque;
      RANKINGS:1-5,LVF(Priority);
      PARAMETERS:1, 2.500:
                 2, 2.375:
                 3, 2.250:
                 4, 2.125:
                 5, 2.000:
                 6, 4.5764:
                 7, 1.58:
                11, 1.4743,  0.1967, 4.1769:
                12, 0.5050,  0.9837, 9.0873:
                13, 0.3581,  0.6316, 8.3796:
                14, 0.2669,  0.3526, 7.2160:
```

```
                15, 0.2633,  0.4824, 7.6123:
                16, 1.7711,  0.1162, 2.5904:
                17, 0.7653,  0.1292, 3.4925:
                18, 0.4005,  0.1944, 2.1849:
                19, 0.3935,  0.1659, 3.8059:
                20, 0.3423,  0.1389, 4.2318:
                21, 1.6535,  0.1864, 1.6298:
                22, 0.7469,  0.1541, 2.0553:
                23, 0.5839,  0.1110, 2.7919:
                24, 0.4578,  0.1829, 2.4253:
                25, 0.3658,  0.2474, 2.6304:
                26, 1.6340,  0.1829, 1.5930:
                27, 0.7832,  0.2071, 1.7831:
                28, 0.5873,  0.2437, 1.9941:
                29, 0.3873,  0.2140, 2.0258:
                30, 0.3840,  0.1738, 2.2151:
                31, 1.4705,  0.1676, 1.5121:
                32, 0.7006,  0.2178, 1.5861:
                33, 0.4600,  0.2676, 1.7138:
                34, 0.3148,  0.2379, 1.7069:
                35, 0.2727,  0.2045, 1.7935;

      SEEDS:1, 5000, c:
            2, 5100, c:
            3, 5200, c:
            4, 5300, c:
            5, 5400, c:
            6, 5500, c:
            7, 5600, c:
            8, 5700, c;
      TALLIES:1, FlowTime:
              2, Lateness:
              3, Tardiness:
              4, Squared Lateness:
              5, Absolute Lateness:
              6, Semi_Quad. Lateness;
     COUNTERS:1, TardyJobs:
               2, AllSelJobs:
               3, SelectedJobs, 2500:
               4, AllJobs;
      DSTATS : NR(1) - MachDown(1), Res 1:
               NR(2) - MachDown(2), Res 2:
               NR(3) - MachDown(3), Res 3:
               NR(4) - MachDown(4), Res 4:
               NR(5) - MachDown(5), Res 5:
               MachDown(1), Dt1:
               MachDown(2), Dt2:
               MachDown(3), Dt3:
               MachDown(4), Dt4:
               MachDown(5), Dt5:
               NQ(1), Queue 1:
               NQ(2), Queue 2:
               NQ(3), Queue 3:
               NQ(4), Queue 4:
               NQ(5), Queue 5;
      REPLICATE,40,0,,NO,YES,20000;

END;
```

B.3 C Code

```
#include <sys/types.h>
#include<stdio.h>
#include "/homes/ac/ie/comlekci/csim/include/simlib.h"

#define max(x,y)  ( (x) > (y) ? (x) : (y) )
#define min(x,y)  ( (x) < (y) ? (x) : (y) )
#define NATTRIBUTE 35

typedef struct tms {
        clock_t tms_utime;                /* user time */
        clock_t tms_stime;                /* system time */
        clock_t tms_cutime;               /* user time, children */
        clock_t tms_cstime;               /* system time, children */
} tms;

struct tms *cpu_1, *cpu_2;
clock_t  mytime;
float ProcessTime;

#include"/homes/ac/ie/comlekci/csim/include/others.c"

void cevent(Lent,Nevt,sim)

smint *Lent;
smint *Nevt;
simstr *sim;

{
   smint  QNum, i, j, Rank, Nqq, OInd, Nop;
   smint  Anum1=11, Anum2=14, Anum3=18, Anum4=13, Anum5=16, Anum6=19;
   float  CoefProc, Psum, prior;

   QNum = m(Lent);
   for(j=1; j<=nq(&QNum); ++j)
     {
       Rank = j;
       Nqq = lrank(&Rank,&QNum);
       CoefProc = (a(&Nqq,&Anum2)-a(&Nqq,&Anum1)) / a(&Nqq,&Anum3);
       OInd = a(&Nqq, &Anum4);
       Psum = 0;
       for(i=1; i<=OInd; ++i)
         {
           Nop = i + 5;
           Psum = Psum + a(&Nqq, &Nop);
         }

       prior = max(((CoefProc*Psum)+a(&Nqq,&Anum1)),
                                      (sim->tnow + a(&Nqq,&Anum5)));
       seta(&Nqq,&Anum6,&prior);
     }
   return;
}
```

Appendix C

ANOVA Tables

Table C.1: Analysis of Variance for Mean Lateness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	19393.7132708	21.52	0.0001	yes
Error	2301	21157.6463109			
A	39	1232.46646663	3.44	0.0001	yes
F	4	2778.57946142	75.55	0.0001	yes
D	2	2733.18309325	148.62	0.0001	yes
B	1	34.69693538	3.77	0.0522	no
U	1	138.84065104	15.10	0.0001	yes
F*D	8	5555.03643508	75.52	0.0001	yes
F*B	4	315.33573275	8.57	0.0001	yes
F*U	4	1759.47246542	47.84	0.0001	yes
D*B	2	80.20364425	4.36	0.0129	yes
D*U	2	1036.85388908	56.38	0.0001	yes
B*U	1	13.86696037	1.51	0.2196	no
F*D*B	8	464.32750575	6.31	0.0001	yes
F*D*U	8	2540.23874758	34.53	0.0001	yes
F*B*U	4	304.64945275	8.28	0.0001	yes
D*B*U	2	75.26082675	4.09	0.0168	yes
F*D*B*U	8	330.70100325	4.50	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table C.2: Analysis of Variance for Mean Tardiness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	41519.2070771	77.31	0.0001	yes
Error	2301	12609.4330469			
A	39	2579.83471563	12.07	0.0001	yes
F	4	5194.08803958	236.96	0.0001	yes
D	2	6953.44144308	634.44	0.0001	yes
B	1	1538.99345704	280.84	0.0001	yes
U	1	9577.49320704	1747.72	0.0001	yes
F*D	8	6500.36485942	148.28	0.0001	yes
F*B	4	245.27803858	11.19	0.0001	yes
F*U	4	1655.12383858	75.51	0.0001	yes
D*B	2	176.65256808	16.12	0.0001	yes
D*U	2	2096.36527858	191.27	0.0001	yes
B*U	1	979.75315204	178.79	0.0001	yes
F*D*B	8	508.37297192	11.60	0.0001	yes
F*D*U	8	2847.43063392	64.95	0.0001	yes
F*B*U	4	207.49715525	9.47	0.0001	yes
D*B*U	2	87.10081658	7.95	0.0004	yes
F*D*B*U	8	371.41690175	8.47	0.0001	yes

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table C.3: Analysis of Variance for Mean Squared Lateness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	6011048329.08	20.00	0.0001	yes
Error	2301	7055310409.12			
A	39	1465578814.59	12.26	0.0001	yes
F	4	135681879.64	11.06	0.0001	yes
D	2	369557911.15	60.26	0.0001	yes
B	1	774845112.43	252.71	0.0001	yes
U	1	1373936694.32	448.09	0.0001	yes
F*D	8	48870804.13	1.99	0.0438	yes
F*B	4	46142849.48	3.76	0.0047	yes
F*U	4	88590555.40	7.22	0.0001	yes
D*B	2	256351164.43	41.80	0.0001	yes
D*U	2	364365142.62	59.42	0.0001	yes
B*U	1	719348184.65	234.61	0.0001	yes
F*D*B	8	17592529.30	0.72	0.6766	no
F*D*U	8	36665014.22	1.49	0.1538	no
F*B*U	4	42581515.06	3.47	0.0078	yes
D*B*U	2	254417037.13	41.49	0.0001	yes
F*D*B*U	8	16523120.51	0.67	0.7152	no

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table C.4: Analysis of Variance for Mean Semi-Quadratic Lateness

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	5189024917.51	17.80	0.0001	yes
Error	2301	6844019801.38			
A	39	1352228439.23	11.66	0.0001	yes
F	4	98687633.52	8.29	0.0001	yes
D	2	342948147.73	57.65	0.0001	yes
B	1	641929029.22	215.82	0.0001	yes
U	1	1048619019.46	352.55	0.0001	yes
F*D	8	31857439.53	1.34	0.2193	no
F*B	4	46690283.82	3.92	0.0035	yes
F*U	4	81893321.04	6.88	0.0001	yes
D*B	2	253375770.76	42.59	0.0001	yes
D*U	2	341212329.79	57.36	0.0001	yes
B*U	1	605169085.40	203.46	0.0001	yes
F*D*B	8	14287449.86	0.60	0.7782	no
F*D*U	8	26154504.32	1.10	0.3605	no
F*B*U	4	43988179.45	3.70	0.0053	yes
D*B*U	2	246280294.80	41.40	0.0001	yes
F*D*B*U	8	13703989.57	0.58	0.7985	no

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

Table C.5: Analysis of Variance for Mean Flowtime

Source	DF	Sum of Squares	F Value	Pr gt F	Significant at 0.05?
Model	98	499178.413081	191.58	0.0001	yes
Error	2301	61178.773204			
A	39	28869.792133	27.84	0.0001	yes
F	4	75.279623	0.71	0.5865	no
D	2	148288.537450	2788.65	0.0001	yes
B	1	15921.586527	598.83	0.0001	yes
U	1	217502.868917	8180.52	0.0001	yes
F*D	8	150.559246	0.71	0.6849	no
F*B	4	5.188148	0.05	0.9955	no
F*U	4	49.167514	0.46	0.7635	no
D*B	2	6781.025317	127.52	0.0001	yes
D*U	2	66958.517244	1259.19	0.0001	yes
B*U	1	9835.871305	369.94	0.0001	yes
F*D*B	8	10.376295	0.05	0.9999	no
F*D*U	8	98.335027	0.46	0.8831	no
F*B*U	4	5.502374	0.05	0.9950	no
D*B*U	2	4614.801213	86.78	0.0001	yes
F*D*B*U	8	11.004748	0.05	0.9999	no

A: Block effect, F: Flowtime estimation method

D: Dispatching rule, B: Shop Balance, U: Utilization

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