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Developing Job Flow Time Prediction Models in the Dynamic Unbalanced Job Shop*

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Abstract

This research addresses flow time prediction in the dynamic unbalanced job shop scheduling environment. The specific purpose of the research is to develop the job flow time prediction model in the dynamic unbalanced job shop. Such factors as job characteristics, job shop status, characteristics of the shop workload, shop dispatching rules, shop structure, etc. are considered in the prediction model. The regression prediction approach is analyzed within a dynamic, make-to-order job shop simulation model. Mean Absolute Lateness (MAL) and Mean Relative Error (MRE) are used to compare and evaluate alternative regression models developed in this research.

1. Introduction

The importance of meeting promised customer due dates in a job shop is well known in the industrial environment and among academic researchers. The prediction of job flow times is in turn crucial in assigning customer due dates as well as in other production shop planning activities. The purpose of this research is to develop and evaluate regression strategies for predicting job flow time in an industrial job shop environment so that due dates can be more accurately set.

Many simulation studies have been reported which address priority decision rules for the dispatching of orders in a job shop. In these studies, the due date assignment procedures have characteristically been somewhat unrealistic. In an actual shop environment many diverse job and

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shop attributes are considered in setting a due date. However, these attributes have not normally been considered in due date assignment procedures used in past simulation research. Such simulation studies simply assign each job a flow allowance based on a rough estimate of job flow time, including a 'safety factor' to absorb the effects of variables that the estimation process does not explicitly consider [29]. These due date assignment methods may have little logical relationship to actual flow time, but can have significant impact on the conclusions of the simulation study. There is evidence that some job shop simulation studies reported in the past have had questionable results due to inconsistent or unrealistic procedures employed to assign the due dates [34].

2. RESEARCH OBJECTIVES

The primary thrust of this research is on the development and evaluation of prediction techniques for job flow time in a dynamic unbalanced job shop. The success of a prediction system depends on the proper identification of how the independent variables of the prediction model impacts job flow time or what forms of job and shop information are most useful in predicting job flow times.

A factorial experimental design is used to evaluate the regression prediction models. In this experiment, different regression prediction models (principal factor) are tested to determine the accuracy of job flow time prediction under the different dispatching rules. 'Accuracy' of the prediction models is measured by the 'discrepancy' between actual job flow times and the predicted flow times. Two alternate performance criteria are used in the experiment: (1) mean absolte lateness and (2) mean relative error.

3. REVIEW OF LITERATURE

The focus of the most computer simulation studies of dynamic job shops in the past two decades has centered on an experimental evaluation of priority dispatching rules. In these studies due dates, when considered, are treated in one of two ways: (1) externally imposed or (2) internally set [30]. In externally imposed due date research there is usually emphasis on scheduling rules which minimize flow times and deviations from the preassigned due dates. Other research assumes internally set due dates and examines the effectiveness of various scheduling rules, given these 'more rational' due dates. Effectiveness is usually measured in terms of lateness or tardiness.

3.1 Determinants of Job Flow Time

Studies [9], [11], [12], [26], [36] indicate that the following factors determine the actual flow time of orders:

1) Shop complexity and design;
2) Job characteristics;
3) Shop utilization (load) and ability to plan and control capacity;
4) Operating decisions such as priority control and labor assignment rules;
5) Other factors such as lot splitting, lap phasing, processing interruptions, rework, and scrap.

Ragatz and Mabert [29] present a conceptual model of due date management in a job shop. The model describes, in general terms, the important factors in flow time prediction.

In summary, job flow time in the dynamic environment is a function of four factors:

1) The characteristics of the job;
2) The dispatching rules used;
3) The shop status;
4) Future job arrivals.

3.2 Classification Schemes

Several classification schemes for due date assignment procedures are found in the literature. Smith and Seidmann [34] identify three basic categories of due date assignment, i.e., flow time prediction procedures on the basis of the way the procedures are developed. Kiran and Smith [19] also classify due date assignment procedures into 'static due date' assignment rules and 'dynamic due dates' assignment rules. Ragatz and Mabert [28], [29] classify the procedures used to set flow time allowances according to the dimension of the complexity and the amount of information about the jobs and the system that is used.

3.2.1 Naive Procedures

Naive flow time prediction procedures are most representative of a situation in which due dates are set externally and independently to the scheduling system. Two examples of such naive procedures are 'Constant' (CON) and 'Random' (RDM). The random rule has often been used as a 'benchmark' from which to assess the relative improvement of other more rational procedures.

3.2.2 Procedure Using Job Characteristic Information

The more sophisticated prediction procedures attempt to refine flow time estimates by using information available on job content or job characteristics. Four models of this type are Total Work (TWK), Number of Operation (NOP), Total Work and Number of Opearations (TWK + NOP), and Slack (SLK).

The TWK procedure has been popular in the research literature [12], [13], [36]. The results of these research studies show that the relationship between flow time and processing time is influenced by factors such as labor and job dispatching rules, capacity, and utilization level of the shop.

Efforts to improve the performance of TWK were attempted by several researchers. Ashour and Vaswani [3] tried combining TWK and NOP by multiplying the processing time by the number of operations. Eilon and Chowdhury [11] considered raising processing time to a power in a TWK-like procedure. Neither of these efforts was successful in improving TWK performance. Kanet [18] developed a variation of TWK and NOP called processing plus waiting (PPW). Baker and Kanet [7] showed that TWK outperformed PPW and NOP with better adherence to due dates and fewer jobs in the system.

Miyazaki [24] considered the relationship between job characteristics and flow time using a statistical approach although the basis of this model have been questioned by Baker and Kanet [7]. In an earlier paper, Fabrycky and Shamblin [14] also used the relationship between number of operations and flow time distribution. Here, however, the relationship was used to control job priority for sequencing rather than due date assignment.

3.2.3 Procedure Using Shop Status Information

Researchers have considered using shop status information in setting due dates. Elison and Chowdhury [11] and Weeks [35] used expected waiting times and current queue lengths to estimate job flow time more accurately. Baker and Bertrand [4] suggested using current shop workload in the due date assignment decision. Ragatz and Mabert [27] demonstrated a methodology to include both job characteristics and shop status information for establishing due dates for a single machine case.

A study that incorporates knowledge of both congestion and job characteristics into the establishment of due dates was performed by Weeks [35]. A due date assignment procedure derived by Weeks [35] in a simulation study of a 24 machine dual constrained shop was based on the number of jobs in the system.

Ragatz and Mabert [30] reported on a comparative analysis of various due date assignment procedures that have been mentioned in the literature by different authors. In their study, eight different procedures for flow time prediction were evaluated. The first three rules use only job chatacteristic information, while the remaining five use both job characteristics and shop status information. The final rule for determining flow time utilized response surface mapping procedures to identify important independent variables and estimate various functional rule equations. This approach was initially investigated by Ragatz and Mabert [27] for the single machine environment. Response Mapping Rule (RMR) thus specifies a set of job characteristics or shop status measures as independent variables. Regression analysis was used to determine the coefficients of the independent variables that minimize the variance of the predicted flow time about the actual flow times. These procedures include TWK, NOP, TWK + NOP, JIQ, WIQ, Weeks' Jobs in the System (WEEKS), JIS, and Response Mapping Rule (RMR).

3.2.4 Procedure Using Future Job Arrival Information

Very little research has considered the impact of future job arrivals on the congestion in the system when setting due dates. Reiter [31] describes a comprehensive simulator which is used in a study that forecasts anticipated loads every two weeks. The forecast loads are then used to set delay parameters for estimating due dates for new projects. However, no comparisons were made between this due date assignment technique and other techniques. Legrande [20], in his simulation of the Huges Aircraft El Segundo job shop, took a simulation approach, using data on current orders to create hypothetical future orders which were then used to simulate future shop load. Legrande did not, however, use the approach to determine appropriate job due dates.

4. REGRESSION APPROACH FOR JOB FLOW TIME PREDICTION

4.1 Independent Variables

The independent variables used in this research are basically concerned with combinations of job characteristic information and shop status information. Shop scheduling theory has suggested the 12 independent variables. The specific independent variables proposed in the prediction models are presented in 〈Table 1〉.

These 12 independent variables can be logically classified into three information categories.

1) Job Characteristic Information : (1) TWK (2) NOP.
2) Job Specific Shop Congestion Information : (3) WIQ (4) JIQ (5) NBO (6) TOPQ (7) TWIQ123.
3) General Shop Congestion Information : (8) WIS (9) JIS (10) TOPS (11) WBQ (12) JBQ

〈Table 1〉 Independent Variables

TWK	Total work hours (processing time) in a job
NOP	Number of operations in a job
WIQ	Work hours currently in queue on a job's routing
JIQ	Jobs currently in queue on a job's routing
TOPQ	Total number of operations in queue on a job's routing
TWIQ123	Total work hours in queue at 1st, 2nd, and 3rd machines on a job's routing
NBO	Number of bottleneck operations on a job's routing
WIS	Total work hours yet to be completed in the system
JIS	Total jobs currently in the system
TOPS	Total number of operations in the system
WBQ	Total work hours currently in the bottleneck queue
JBQ	Total jobs currently in the bottleneck queue

4.2 Multicollilinearity Problems

Mulicollinearity is defined as the violation of the assumption of independence among the independent variables. If high mulicollinearity is present, various difficulties arise. Reduced precision in estimating the coefficients of predictive functions and increased difficulty in isolating the separate effects of each independent variables on the dependent variable may take place. Independent variables may be dropped incorrectly (perhaps mechanically so in stepwise regression procedures) not because the parameter estimates are too small but because the standard errors are too large [17]. Thus, high multicollinearity in a set of independent variables makes inappropriate one of the fundamental purposes of regression analysis, structural interpretation.

The degree of concern over multicollinearity depends on the purpose in employing regression analysis. If the purpose is explanation between independent variables and dependent variable, then one should be very concerned with high multicollinearity. However, if the results are used for prediction, multicollinearity is not as serious a problem. Reduction of multicollinearity may not be necessary for prediction, if the independent variables which are correlated in the sample are found to be correlated consistently in other samples in other time periods. This is presumed to be the scenario in this research.

4.3 Autocorrelation Problems

Error terms correlated over time are said to be autocorrelated or serially correlated. In this research, job flow times intuitively have a serial correlation and error terms in the regression model may be serially correlated. As such, the assumption of uncorrelated or independent error terms in the regression model may not be appropriate.

It should be noted that autocorelation in time series data and the serial correlation in job flow times are different in some aspects. First, time series data are usually observed and measured with a fixed and constant time interval. In this research, the order of the observations in job flow times is important because of their serial dependence. However, job flow times are not observed and measured on fixed and constant time intervals. Since the time series data are observed on equal time intervals, time is an interval scale variable and is one of the factors having an influence on the autocorrelation of time series data. However, for the serial correlation in job flow times in this research, time is only an ordinal scale.

If the error terms in the regression model are positively autocorrelated, the regression parameters estimated by the ordinary least squares procedure are still unbiased, but they no longer have the minimum variance property and may be quite inefficient. Job flow times intuitively have a serial correlation. Thus, if autocorrelation goes undetected, the confidence intervals and tests using the t and F distributions are no longer strictly applicable. In this research, residual plots and the Durbin-Watson test are used to detect the presence of autocorrelation.

When it appears that autocorrelation in errors exists, it is necessary to recognize explicitly the autrocorrelative structure in the model and devise an appropriate parameter estimation method instead of the OLS method. This could be done by using either the method due to Cochrane and Orcutt [8] or by using 'weighted least squares' as suggested by Draper and Smith [10]. The latter is called the generalized least squares (GLS) by Montegomery and Peck [25]. In this research, when faced with autocorrelation, the weighted least square method is employed.

4.4 Regression Model Development and Validation

4.4.1 Model Development

In developing prediction models, one of the most important research tasks is variable selection. Two key aspects of the variable selection problem are generating the models that include only a subset of the independent variables (subset models) and deciding if one subset is better than another. The specific computational technique employed in this research for variable selection is the 'all possible subset models' approach. The criteria for evaluating and comparing subset models used in this research are residual means square (MSE) and Mallows' Cp statistics [21], [22], [23].

4.4.2 Model Validation

The objective of the validation stage in this research is to select the one final version for each regression model among the candidate models. Allen's [1], [2] PRESS statistic is considered as a form of 'data splitting' for model validation.

The PRESS statistic is useful in evaluating alternative models when the objective is prediction. However, the PRESS statistic does not consider the model complexity, i.e., the number of independent variables retained in the model. In this research, PRESS adjusted for the model complexity (APRESS) is devised as a criterion to select the final model. APRESS is calculated as follows:

$$APRESS = \frac{PRESS}{n-p}$$

where n is the number of observations;

p is the number of independent variables retained for the candidate model.

A value of APRESS will be calculated for each model under consideration. The model with the smallest value of APRESS will be selected.

5. RESEARCH DESIGN

The production shop simulation model is programmed in the SIMAN language. Five different regression models are developed that combine job characteristic and shop status variables in various forms. The regression prediction approach described in the previous section are applied in a simulated, dynamic unbalanced job shop. The five regression prediction models are compared under various job dispatching rules in a factorial experiment.

5.1 Job Shop Simulation Environment

The followings are the major features of the simulation model used in this research. The simulated job shop consists of eight unique machines. Jobs arrive dynamically and are released into the shop upon arrival. The interarrival pattern of jobs follows an exponential distribution. The mean interarrival time can be adjusted to maintained the 75% shop utilization level. Processing times are generated from an exponential distribution. The number of job operations is generated randomly to be either 4, 6, or 8. The simulated shop has a single 'bottleneck' machine operating at about 96% capacity. The number of bottleneck operations for each job is randomly generated to be 0, 1, or 2. The location of the bottleneck operation in a job routing is determined randomly.

Three different job dispatching rules are considered in this research. The three dispatching rules are: (1) First Come-First Served (FCFS), (2) Shortest Processing Time (SPT), and (3) Minimum Slack (MINSLK). These rules represent the three major dispatching rule strategies: random, static, and dynamic.

5.2 Regression Prediction Models

Five different flow time prediction models using regression were identified and developed for evaluation. The fundamental approach of each prediction model involves estimating the flow time of job i ($FLOW_i$), and adding this estimate to the job's arriving time (ATi) to determine the due date of job i ($DDATE_i = AT_i + FLOW_i$).

The prediction models are designed to utilize combinations of 1) job characteristics, 2) job specific shop congestion, and 3) general shop congestion information in estimating expected job flow time. The prediction models are described as follows:

5.2.1 Prediction model with job characteristic information only (JC)

A typical example of JC prediction model is Total Work (TWK): $FLOW_i = kP_i + C$. This rule, developed previously in the literature, was employed as a benchmark to evaluate the other four more complex prediction models.

5.2.2 Prediction model with job characteristic and job specific shop congestion information (JC/JS)

Typical example of JC/JS prediction models are Total Work (TWK) plus Work in Queue(WIQ): $FLOWi = k1P_i + k2(WIQ_i) + C$. At the time job i is released to the shop, the specific work center queues on the routing for job i are polled for the total work hours in queue (WIQ_i). This job specific shop congestion information is then combined with the total job processing time (P_i) to predict flow time.

5.2.3 Prediction model with job characteristic and general shop congestion information (JC/GS)

Typical example of JC/GS prediction models are Total Work (TWK) plus Work in system (WIS): $FLOW_i = k1P_i + k2(WIS_i) + C$. At the time of job i is released to the shop, all the work centers in the system are polled for the total work in the system. This general shop congestion information is then combined with the total processing time (P_i) to estimate flow time for job i.

5.2.4 Prediction Model with Job Characteristic, Job Specific Shop Congestion, and General Shop Congestion Information (JC/JS/GS)

This JC/JS/GS prediction model combines all three kinds of information and includes a single variable from each information category. The model is compared with the JC/JS and the JC/GS models to determine whether the inclusion of both job specific shop congestion information and general shop congestion information in the same model can improve prediction accuracy.

5.2.5 All Variable Multiple Regression Model (AVMR)

The AVMR model considers subsets of all 12 independent variables working together. The AVMR model is developed to determine whether such a complex model can improve prediction accuracy.

5.3 Research Plan

The research for the regression approach follows a four-stage process.

Stage 1: Computer Simulation and Data Generation

The computer simulation model is written and validated. A simulation run is made under each experimental condition to provide the necessary data for prediction model estimation and evaluation. This sample database is divided into two parts: 1) an estimation part 2) an evaluation part.

The estimation part of the data is utilized for the model development and model validation. The evaluation part is used in the experimental design to test the five regression models for flow time prediction. The evaluation part of the data is divided into five segments of jobs for analysis purposes, i.e., each segment of jobs represents an observation in the experimental design. Each segment consists of 2000 observations.

Stage 2: Candidate Model Development

The objective of the model development stage is to generate candidates for each of the five regression models on the basis of the estimation part of the data. In developing candidate regression models, the 'all possible subset models' approach is used. Two criteria, i.e., residual mean square (MSE) and Mallows' C_p statistic, are employed to evaluate and compare subset models by the all possible subset models approach. If the same model is selected based on the MSE and C_p criteria, the models which has the second minimum MSE and C_p statistics are also selected.

The JC prediction model, employed primarily as a benchmark, has only two candidate models, one using the TWK variable and one using the NOP variable. The all possible subset models approach results in 10 (2 x 5) candidates for the JC/JS model, 10 (2 x 5) candidates for the JC/GS model, 50 (2 x 5 x 5) candidates for JC/JS/GS model, and $2^k - 1$ candidates for AVMR model.

Stage 3: Model Validation

The candidates for each regression model developed in stage 2 are validated. The objective of the model validation stage is to select the more accurate prediction model of the alternative candidates developed in the model development stage. Allen's [1], [2] model validation technique is used, i.e., predicted error sum of squares, or PRESS. In this research, PRESS adjusted for the model complexity (APRESS) is devised as a criterion to select the final model.

Stage 4: Evaluation

A two factor factorial experimental design is performed to evaluate the five flow time prediction regression models using the evaluation part of the data. In this experiment, the principal factor is the prediction model and the environmental factor is dispatching rule.

5.4 Experimental design

5.4.1 Performance Measure

Since the major thrust of this paper is to determine which flow time prediction model provides the most accurate method of setting due dates, a statistic was used that measures both positive and negative deviations of job completion times from job due dates. The primary accuracy measure used in this research is Mean Absolute Lateness (MAL), defined as:

$$\mathrm{MAL} = \sum_{i=0}^{n} |L_i|/n$$

where L_i = actual flow time of job i - prediction flow time of job i.

Mean Relative Error (MRE) is also used to evaluate the prediction models as a relative performance criterion. MRE is the mean ratio of absolute error to actual flow time. The smaller the value, the better the performance of the model. MRE is composed as follows:

$$\mathrm{MRE} = [\sum_{i=0}^{n} |Li|/\ Ai\ ]/n$$

where A_i = actual flow time of job i.

5.4.2 Experiments

Five different regression prediction models are finally selected and evaluated. To compare the five prediction models, ANOVA with split plot design is planned. Considering all factors and levels, there are 15 (3 dispatching rule x 5 prediction models) simulation experiments to be run. For each experiment, performance of the model is measured over five replications from the evaluation part of the data. For each dispatching rule, common random number seeds will be used in order to reduce variance in the experiment [15].

ANOVA with split plot design is the appropriate statistical tool to evaluate the performance of the five prediction models becuase the same test data within the dispatching rule are applied to every prediction model (i.e., common random number seeds). In the context of the ANOVA with split plot design, a multiple comparison test is then applied to evaluate performance differences among the regression prediction models.

6. RESULTS

6.1 Preliminary Analysis

A cross correlation analysis and factor analysis for each combination of the dispatching rule and the 75% shop congestion level was conducted to examine the interrelationships among the 12 independent variables. 〈Table 2〉 and [Figure 1] show the cross correlation matrix and the results from the factor analysis for the independent variables at the 75% shop utilization level for the FCFS dispatching rule. Other results for the SPT and the MINSLK dispatching rules are very similar to those of the FCFS dispatching rule although the results are not presented here. [Figure 1] also show the loadings of each independent variable on the factors identified by the factor analysis.

〈Table 2〉 Independent Variable Cross Correlation Matrix
75% Shop Utilization and FCFS Dispatching Rule

	TWK	NOP	WIQ	JIQ	TOP Q	TWI Q123	NBO	WIS	JIS	TOPS	WBQ	JBQ
TWK	100											
NOP	55	100										
WIQ	12	21	100									
JIQ	7	1	95	100								
TOPQ	11	17	95	98	100							
TWIQ123	-8	-17	65	71	68	100						
NBO	-4	-3	53	58	55	44	100					
WIS	8	5	58	57	60	41	-2	100				
JIS	2	2	58	61	60	44	-1	96	100			
TOPS	5	5	57	59	61	42	-2	98	98	100		
WBQ	2	3	55	54	53	39	-1	80	85	83	100	
JBQ	1	2	53	58	57	43	0	82	90	87	95	100

Note : Correlation Coefficients have been multiplied by 100 and rounded to the nearest integer

From the independent variable correlation matrix and the factor analysis, the following observations are made:

(1) Interrelationships among 12 variables are stable across the dispatching rules used. That is, the interrelationships among 12 variables are not sensitive to the dispatching rule.

(2) The results from the factor analysis confirm the existence of distinct groupings among the independent variables. Also, these results empirically support the logical classification of the 12 independent variables into the three categories described in the previous section.

The simple regression coefficients and R2 values for each of the 12 independent variables for the 75% shop utilization levels using each dispatching rule are calculated based on a single replication of 2000 jobs. The coefficients of the 12 independent variables are estimated by the weighted least square for autocorrelation.

From the preliminary analysis of individual relationships between the actual flow times and the independent variables in ⟨Table 3⟩, the following observations are mode:

(1) Under the FCFS and the MINSLK dispatching rules, the R2 values are highest for the job specific shop congestion variables, and lowest for the job characteristic variables. The job specific shop congestion variables appear to be the most important variables for a regression prediction model under the FCFS and the MINSLK dispatching rule. However, under the SPT dispatching rules, job characteristic information is more important than job specific shop congestion information or general shop congestion information.

(2) All 12 independent variables have low regression R2 values under the SPT dispatching rules compared to the FCFS and the MINSLK dispatching rules. The highest R2 values for any independent variable under the SPT dispatching rule is 0.14. However, the highest R2 values under the FCFS and the MINSLK dispatching rule are 0.86 and 0.69, respectively.

	Factor 1	Factor 2	Factor 3
JIS	96*	21	0
TOPS	95*	21	4
WIS	93*	20	6
JBQ	92*	20	-1
WBQ	90*	18	0
JIQ	44	87*	9
TOPQ	45	85*	15
NBO	-23	85*	-6
WIQ	43	83*	19
TWIQ123	31	73*	-22
NOP	1	4	89*
TWK	2	0	86*

Note : Values are multiplied by 100 and rounded to the nearest integer.
Values greater than 70 have been identified by an '*'.

⟨Figure 1⟩ Variable Groupings
75% Shop Utilization and FCFS Dispatching Rule Rotated Factor Pattern

〈Table 3〉 Linear Regression Relationships
(Job Characteristic Variables)

75% Utilization Level				
Variable	Dispatching Rule	a	b	R^2
TWK	FCFS	1.89	29.6	0.04
	SPT	3.3	−1.4	0.14
	MSLK	2.19	25	0.09
NOP	FCFS	3.7	18.5	0.05
	SPT	2.15	5.25	0.02
	MSLK	2.92	20.4	0.05
WIQ	FCFS	0.89	5.38	0.86
	SPT	0.12	12.9	0.03
	MSLK	0.72	11.8	0.68
JIQ	FCFS	0.89	12.3	0.84
	SPT	0.48	12.5	0.03
	MSLK	0.71	17.5	0.68
TOPQ	FCFS	0.25	7.89	0.84
	SPT	0.12	10.9	0.03
	MSLK	0.16	15	0.69
TWIQ123	FCFS	0.91	25.9	0.41
	SPT	0.39	15.8	0.01
	MSLK	0.75	26.9	0.35
NBO	FCFS	17.7	22.9	0.28
	SPT	3.34	14.8	0.01
	MSLK	10.2	27.6	0.15
WIS	FCFS	0.23	4.63	0.32
	SPT	0.06	11.1	0.02
	MSLK	0.19	4.94	0.46
JIS	FCFS	0.82	5.98	0.32
	SPT	0.36	10.6	0.01
	MSLK	0.84	4.81	0.44
TOPS	FCFS	0.23	4.69	0.32
	SPT	0.1	10.5	0.01
	MSLK	0.19	5.23	0.45
WBQ	FCFS	0.99	19.2	0.29
	SPT	0.11	15.2	0.01
	MSLK	1.01	18.8	0.35
JBQ	FCFS	0.93	20.8	0.29
	SPT	0.5	14.7	0.01
	MSLK	0.92	20.6	0.36

Note : $Y = aX + b$

6.2 Prediction Models

6.2.1 JC Prediction Model

〈Table 4〉 summarizes the JC prediction model selected under each combination of dispatching rule and 75% shop congestion level along with the estimated parameters for each model. For the JC prediction model, the TWK variable is consistently selected over the NOP variable. This

〈Table 6〉 summarize the best JC/GS prediction models and their estimated parameters for each dispatching rule under the 75% shop utilization.

TWK and WIS were selected in combination to form the best model in terms of APRESS statistic except under the FCFS dispatching rule. In this experimental setting, TWK and JIS were selected rather than TWK and WIS. None of JC/GS prediction model includes TOPS, JBQ, and WBQ variables. This supports the fact that in general, the total work hours in system (WIS) or the number of jobs in system (JIS) information are more useful than the total number of operations in system (TOPS) or bottleneck information (WIQ and JBQ) when combined with job characteristic information.

For the FCFS and the MINSLK dispatching rules, the JC/GS prediction model shows substantial improvement by adding a general shop congestion variable (WIS or JIS) compared to the JC prediction model. However, this improvement is smaller than the improvement offered by the JC/JS prediction model. For the SPT dispatching rule, the regression R^2 was improved over the JC model only 1% by adding a general shop congestion variable in the JC/GS prediction model. This marginal improvement under the SPT dispatching rule appears to be negligible for practical purposes. This means that the general shop congestion information does not make a contribution in predicting flow time under the SPT dispatching rule while it does make a contribution under the FCFS and the MINSLK dispatching rules.

〈Table 6〉 JC/GS Prediction Models
Unbalanced Shop Environment
(Jobs with Three Different Number of Bottleneck Operations)

	75% Utilization	R2 / MSE / RE
FCFS	(1.80)TWK + (0.79)JIS + (-3.66)	0.34 / 492.1 / 0.53
SPT	(3.26) TWK +(0.05)WIS + (-6.37)	0.15 / 591.1 / 1.16
MINSLK	(1.88) TWK +(0.18)WIS + (-4.63)	0.51 / 226.7 / 0.39

Note: MSE - Mean Square Error

RE - Relative Error = $\sqrt{MSE}$ / Mean Flow Time

6.2.4 JC/JS/GS Prediction Model

6.2.5 AVMR Model

All twelve independent variables were considered in developing the AVMR prediction model. In this model, multiple variables from each of the three information categories can appear in the AVMR models. 〈Table 8〉 summarizes the best AVMR model for each experimental setting and the estimated model parameters.

〈Table 7〉AVMR Prediction Models
Unbalanced Shop Environment
(Jobs with Three Different Number of Bottleneck Operations)

	75% Utilization	R2 / MSE / RE
FCFS	(1.0)TWK	
	+ (0.66) NOP	
	+ (2.16)NBO	
	+ (0.19)WBQ	
	+ (0.43) JIQ	0.89
	+ (0.38)WIQ	82.0
	+ (−0.36)JIS	0.22
	+ (0.02)WIS	
	+ (0.05)TOPS	
	+ (0.06)TWIQ123	
	+ (−0.74)	
SPT	(3.87)TWK	
	+ (−2.22)NOP	0.17
	+ (1.94) NBO	558.8
	+ (0.09)TOPQ	1.13
	+ (1.43)	
MINSLK	(1.67)TWK	
	+ (0.30)NOP	
	+ (1.96) NBO	
	+ (0.12)WBQ	0.81
	+ (0.69) JIQ	89.5
	+ (0.15)WIQ	0.25
	+ (−0.55)JIS	
	+ (0.10)WIS	
	+ (−0.09)TOPQ	
	+ (0.10)TOPS	
	+ (0.08) TWIQ123	
	+ (−4.76)	

Note: MSE - Mean Square Error

RE - Relative Error = $\sqrt{MSE}$ / Mean Flow Time

To select the variables among 12 independent variables, the all possible subset models approach is used. This procedure requires the development of all models involving one candidate independent variable, then two candidate variables, and so on. The criteria for evaluating and comparing subset models are the MSE and Mallows CP statistics. That is, two subset models are selected based of these criteria. If there is a tie, the next best subset model for each criterion are also selected as candidates for the best model. Among these candidate models, a single best model is selected based upon the APRESS statistic.

AVMR models at all experimental settings show marginal improvement for R^2 compared to the JC/JS prediction models. This means that only a few variables are relevant in improving the model, and the two variable models may work as well as the AVMR models to predict flow times. The AVMR model certainly provides very little improvement over the JC/JS/GS (or three variable) model.

Several of the coefficients of the AVMR models in ⟨Table 8⟩ are negative. Such a finding does not seem logical and is best explained as perhaps due to multicollinearity. Multicollinearity occurs when the independent variables are themselves correlated. Pairwise intercorrelations among the 12 independent variables for the FCFS dispatching rule are presented in the correlation matrices in ⟨Table 2⟩.

6.3 Regression Model Evaluation

Each regression model was tested in a set of experiments involving the evaluation part of the data. The evaluation data set consists of five replications of 2000 jobs each. Therefore, each model was used to predict 10000 job flow times. Relevant evaluation criteria include mean absolute lateness and mean relative error.

6.3.1 Mean Absolute Lateness (MAL)

The results of the Analysis of Variance with a spilt plot design for mean absolute lateness (MAL) is shown in ⟨Table 9⟩. ⟨Table 9⟩ shows that the prediction model and the dispatching rule have significant main effects at the 0.05 level. However, the main effects of these experimental factors cannot be interpreted directly since there are significant interaction effects among the experimental factors. Since the major thrust of this research is on the performance of the job flow time prediction models under the different dispatching rules, interaction effects involving the flow time prediction model must be examined.

The result of the ANOVA for the MAL performance measure shows that there are significant interaction effects at the 0.05 level between the prediction model and the dispatching rule (PR by DR). That is, the MAL performance of the prediction model depends on the dispatching rule employed.

<Table 8> Analysis of Variance for Split Plot Design - MAL
Dependent Variable : Mean Absolute Lateness (MAL)

Source of Variance	DF	Sum of Squares	F Value	PR > F
Prediction Model (PR)	4	1087.70	156.45	0.0001
PR by RP	16	27.81	1.29	0.2235
Dispatching Rule (DR)	2	65.27	5.79	0.0279
DR by RP	8	45.08	4.19	0.0003
PR by DR	8	662.54	111.20	0.0001
PR by DR by RP	32	23.83	0.55	0.9684

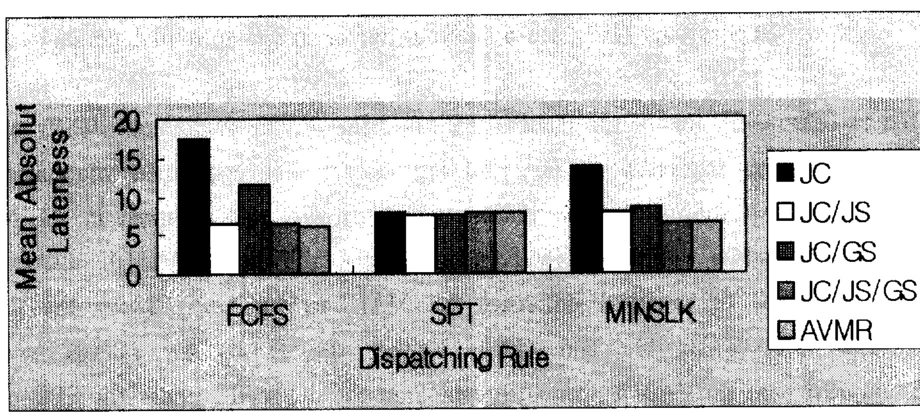
Note: Replications (RP) are a blocking factor in the split plot design

As noted in [Figure 2], for all the dispatching rules, the JC/JS model consistently outperforms the JC/GS model. This reinforces the fact that job specific shop congestion information is more useful than the general shop congestion information. This was also observed in the preliminary analysis of the individual variables. However, under the SPT and MINSLK dispatching rule, there is no statistical or practical difference for MAL performance between the JC/JS and JC/GS models (see <Table 11> and <12>). Neither the JC/JS nor JC/GS models show significant improvement in MAL performance compared the JC model under the SPT dispatching rule. This means that the job specific shop congestion variables and the general shop congestion variables do not improve the MAL performance of the prediction model and are not useful in predicting the flow time under the SPT dispatching rule when combined with the job characteristic variables.

Under the FCFS and the MINSLK dispatching rules, the AVMR model consistently yields slightly better MAL performance among the JC/JS, JC/JS/GS and AVMR models although there is no statistical difference in the MAL performance for all experimental settings (see <Table 10> and <12>). However, the more complex AVMR model shows only marginal improvement for the MAL performance compared to the simpler models (JC/JS and JC/JS/GS) under the FCFS and the MINSLK dispatching rules.

Under the SPT dispatching rule, all five models yield similar Mal performance (see [Figure 2]), i.e., there is no statistically significant difference among the five models (see <Table 11>).

This means essentially that the TWK variable is the most important variable under the SPT dispatching rule and adding any other factors, i.e., job specific shop congestion or the general shop congestion variables, to the JC prediction model does not improve the MAL performance. This is also observed in the preliminary analysis. That is, under the SPT dispatching rule, TWK has the highest R^2 value and all other variables have very low R^2 values (see ⟨Table 3⟩). Also noteworthy, under the SPT dispatching rule, the JC and JC/GS models actually provide better MAL performance than they do under the FCFS (see [Figure 2]). This means that the job characteristic variable, i.e., TWK, works better under the SPT dispatching rule than it does under the FCFS and the MINSLK dispatching rules. Once again however, the JC/JS, JC/JS/GS, and AVMR models under the SPT dispatching rule yield relatively poor performance compared to the FCFS and the MINSLK dispatching rules (see [Figure 2]).



[Figure 2] Mean Absolute Lateness (MAL) -75% Shop Util

⟨Table 9⟩ Tukey's Range Test of Flow Time Prediction Models - MAL
75% Utilization and FCFS Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	17.59	JC
B	11.62	JC/GS
C	6.6	JC/JS
C	6.48	JC/JS/GS
C	6.12	AVMR

<Table 10> Tukey's Range Test of Flow Time Prediction Models - MAL
75% Utilization and SPT Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	7.99	JC
A	7.91	AVMR
A	7.84	JC/JS/GS
A	7.6	JC/GS
A	7.58	JC/JS

<Table 11> Tukey's Range Test of Flow Time Prediction Models - MAL
75% Utilization and MINSLK Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	13.69	JC
B	8.58	JC/GS
B	7.88	JC/JS
B	6.58	JC/JS/GS
B	6.36	AVMR

6.3.2 Mean Relative Error (MRE)

The ANOVA results for the mean relative error performance measure (MRE) are shown in <Table 13>. <Table 13> shows that interaction effect between prediction model and the dispatching rule is significant at the 0.05 level. Prediction model performance depends on the dispatching rule since interaction effect (PR by DR) is significant at the 0.05 level. Tables <14> through <16> illustrate the results of multiple comparison under the combination of three dispatching rules with respect to MRE performance measure.

As noted in [Figure 3], under the FCFS and the MINSLK dispatching rules, the JC/JS, JC/JS/GS, and AVMR models yield better MRE performance compared to the JC and JC/GS models. However, there is no statistical difference in the MRE performance among these three prediction models except under the MINSLK dispatching rule (see <Tables 14> and <16>).

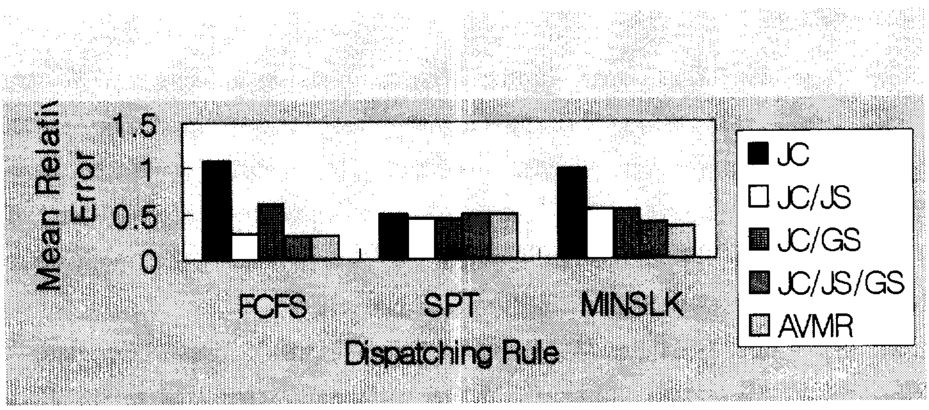
As can be seen in [Figure 3], the MRE performance of the JC/JS, JC/JS/GS, and AVMR models under the FCFS dispatching rule is better than those under the MINSLK dispatching rule although the MAL performance of JC/JS, JC/JS/GS, and AVMR models under the FCFS and the MINSLK dispatching rule is similar. This is partially due to the fact that the MINSLK dispatching rule generates smaller flow time on the average than the FCFS dispatching rule.

〈Table 12〉 Analysis of Variance for Split Plot Design - MRE
Dependent Variable : Mean Relative Error (MRE)

Source of Variance	DF	Sum of Squares	F Value	PR > F
Prediction Model (PR)	4	4.93	90.07	0.0001
PR by RP	16	0.22	1.37	0.1784
Dispatching Rule (DR)	2	0.21	10.45	0.0059
DR by RP	8	0.08	0.01	0.4338
PR by DR	8	3.52	155.45	0.0001
PR by DR by RP	32	0.09	0.28	0.9999

Note: Replications (RP) are a blocking factor in the split plot design

[Figure 3] show that the MRE performance of JC/JS, JC/JS/GS, and AVMR models under the SPT dispatching rule is very poor compared to the FCFS and the MINSLK dispatching rules. The best MRE performance under the SPT dispatching rules is 0.45. However, the best MRE performance under the FCFS or the MINSLK dispatching rule is 0.25 (see 〈Tables 14〉 through 〈16〉).



[Figure 3] Mean Relative Error(MRE) -75% Shop Util.

〈Table 13〉 Tukey's Range Test of Flow Time Prediction Models - MRE
75% Utilization and FCFS Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	1.07	JC
B	0.06	JC/GS
C	0.27	JC/JS
C	0.26	JC/JS/GS
C	0.25	AVMR

〈Table 14〉 Tukey's Range Test of Flow Time Prediction Models - MRE
75% Utilization and SPT Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	0.5	AVMR
A	0.49	JC/JS/GS
A	0.49	JC
A	0.45	JC/GS
A	0.45	JC/JS

〈Table 15〉 Tukey's Range Test of Flow Time Prediction Models - MRE
75% Utilization and MINSLK Dispatching Rule

Alpha = 0.05

Tukey Grouping	Mean Value	Prediction Model
A	0.99	JC
B	0.55	JC/GS
B	0.53	JC/JS
C	0.39	JC/JS/GS
C	0.36	AVMR

7. CONCLUSIONS

The primary purpose of this research was to develop and evaluate five job flow time regression prediction models that employ different types of job characteristic, job specific shop congestion, and general shop congestion information to predict effective completion times in the dynamic and unbalanced job shop environment. The performance of the five different types of regression prediction models has been tested using computer simulation experimentation under the 75% shop utilization and the three different dispatching rules.

Statistical analysis indicates that for the two performance measures considered in this research, the interaction effects between the regression prediction model and the dispatching rules are significant. The implication of these interaction effects is that prediction model performance is dependent on the dispatching rule used.

Under the FCFS or the MINSLK dispatching rule, those prediction models that use both job characteristic and shop status information (JC/JS, JC/GS, JC/JS/GS, and AVMR) perform better for all performance measures than a benchmark model using job characteristic information only (i.e., JC model). Thus shop status information can be used to improve simple job flow time prediction models using only job characteristic information. This finding dramatically highlights the need for shop managers to set due dates based on current conditions at the machine centers required by an incoming job, rather than setting due dates based upon the work content of a job.

Under the SPT dispatching rule, all five prediction models yield similar performance in all performance measures. The use of shop status information, i.e., the JC/JS, JC/GS, JC/JS/GS, and AVMR, provide only marginal improvement or worse performance than the JC model. In general, a prediction model employing only job characteristic information (JC), performs as well as other more complex models. The performance of the best prediction models (JC/JS, JG/JS/GS, and AVMR) under the SPT dispatching rule was generally poor compared to the performance of prediction models under the FCFS and the MINSLK dispatching rules.

The JC/JS model is shown to be consistently superior to the JC/GS model. This means that job specific shop congestion information, i.e., information about work center congestion along a job's routing is more useful information than general shop congestion information. The use of more detailed information like JC/JS/GS and AVMR, provides only marginal improvement or worse performance in some situations, than the JC/JS model. Therefore, a simple combination of job characteristic and job specific shop congestion information, i.e., JC/JS model, performs as well as the more complex model (AVMR) for all performance measures.

The inclusion of bottleneck information variables (WBQ, JBQ, and NBO) did not improve (and therefore were not used in) most of the regression models. This does not necessarily mean that bottleneck information is not important in flow time prediction, but rather that adequate bottleneck information is already included in the job specific shop congestion variables for the jobs which visit the bottleneck work center. For the nonbottleneck jobs, bottleneck information is a subset of general shop congestion information.

Specific bottleneck information is relatively more important under th SPT dispatching rule than the FCFS and the MINSLK dispatching rules. The JC/JS/GS model under the SPT dispatching rule includes the NBO variable. Once again, prediction models under the SPT dispatching rule are generally poor.

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