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Scheduling a dynamic job shop production system with sequence-dependent setups: An experimental study

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Abstract

This paper presents the salient aspects of a simulation-based experimental study of scheduling rules for scheduling a dynamic job shop in which the setup times are sequence dependent. A discrete event simulation model of the job shop system is developed for the purpose of experimentation. Seven scheduling rules from the literature are incorporated in the simulation model. Five new setup-oriented scheduling rules are proposed and implemented. Simulation experiments have been conducted under various experimental conditions characterized by factors such as shop load, setup time ratios and due date tightness. The results indicate that setup-oriented rules provide better performance than ordinary rules. The difference in performance between these two groups of rules increases with increase in shop load and setup time ratio. One of the proposed rules performs better for mean flow time and mean tardiness measures.

Keywords: Dynamic job shop scheduling; Sequence-dependent setup; Simulation; Scheduling rules; Regression metamodel

1. Introduction

Scheduling is the allocation of resources for performing a set of tasks [1]. Resources may be machines in a shop floor, runways in an airport, crews at a construction site or processing units in a computing environment [2]. Tasks may be operations in a shop floor, takeoffs and landing in an airport, stages in a construction project or computer programs to be executed. Proper scheduling leads to increased efficiency and capacity utilization, reduced time required to complete tasks and consequently increased profitability of an organization.

The dynamic job shop scheduling problem (DJSSP) is described as follows [3]. The job shop consists of M machines (work stations) and jobs arrive continuously over time. Each job requires a specific set of operations that need to be performed in a specified sequence (routing) on the machines and involves certain amount of processing time. The job shop becomes a queuing system: a job leaves one machine and proceeds on its route to another machine for the next operation, only to find other jobs already waiting for the machine to complete its current task, so that a queue of jobs in front of that machine is formed. Hence, DJSSP essentially involves deciding the order or priority for the jobs waiting to be processed at each machine to achieve the desired objectives. Scheduling rules or dispatching rules are used for this purpose. Blackstone et al. [4] have presented a review of dispatching rules that are used in job shop scheduling.

One of the standard assumptions in DJSSP is that setup times are included in the processing times. Setup involves the activities such as preparing a machine or workstation to perform the next machining operation. Setups may depend upon the type of job, the type of machine or both. Setup time is defined as the time interval between the end of processing of the current job and the beginning of processing of the next job. Setup time is encountered in manufacturing firms such as printing, plastics manufacturing, metal and chemical processing, paper industry, etc. The typical case in DJSSP is sequence-dependent setup times, where the setup time depends on the job previously processed. A typical example

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is the manufacturing of different colors of paint. In such cases, improving the schedules by as little as 1% can have a significant financial impact.

The traditional approaches in dealing with setup times are that, either to neglect or to include the setup times in the processing times so as to simplify the problems. These approaches would reduce the complexity of the problem, but often lead to unrealistic results. In the literature on job shop scheduling, attempts have been made to address the problem of sequence-dependent setup times. Further, many of these research works do address the static case of job shop scheduling. Yang [5] presents a review of static scheduling research in which the setup time or cost is of main concern. Allahverdi et al. [6] provide a comprehensive review of the literature on scheduling problems involving setup times (costs). They classify scheduling problems into batch and non-batch, sequence-independent and sequence-dependent setup, and categorize the literature according to the shop environments of single machine, parallel machines, flow shops, and job shops. Mathematical programming methods such as traveling salesman problem algorithm and branch and bound algorithm have been used for solving the static job shop scheduling problem with sequence-dependent setup times [7–13]. Even solving small size problems using these algorithms requires a lot of computational efforts under more restrictive assumptions. Chan et al. [14] present an assignment and scheduling model using genetic algorithm-based approach to study the effect of machining flexibility. The operations–machines assignment problem has also been solved by Chan et al. [15] in a flexible job shop, which is a variant of the classical job shop.

Experimentation with computer simulation models makes it possible to compare alternative scheduling rules, test broad conjunctures about scheduling procedures and develop greater insight into the job shop operation. Ramasesh [16] provides a state-of-the-art survey of the simulation-based research on dynamic job shop scheduling. Chan et al. [17] present a review of scheduling studies of flexible manufacturing systems (FMS) which employ simulation as an analysis tool. Chan and Chan [18] present an approach known as pre-emptive approach for the dynamic scheduling of an FMS. In this approach, the dispatching rule (scheduling rule) is changed at a frequency that is varied by the quantity of output produced by the system. Chan and Chan [19] in their paper, report on a simulation study aimed at evaluating the performance of an FMS subject to different control strategies, which include routing flexibilities and dispatching rules. Chan et al. [20] provide an analysis of dynamic dispatching rules for an FMS. There have been a few attempts to study the DJSSP with sequence-dependent setup times. Kim and Bobrowski [21] present a simulation study of a dynamic job shop when sequence-dependent setups exist. The study classifies and tests scheduling rules by considering whether setup time and due date information are used. These scheduling rules are evaluated in dynamic scheduling environments characterized by due date tightness, setup times and cost structure.

This paper focuses on a simulation-based experimental study of scheduling rules for scheduling a typical job shop in which the setup times are sequence dependent. A discrete event simulation model of the job shop system is developed for the purpose of experimentation. Seven scheduling rules from the literature are incorporated in the simulation model. Five new setup-oriented scheduling rules are proposed and implemented. The performance measures considered for analysis are mean flow time, mean tardiness, mean setup time and mean number of setups. The remaining sections of the paper are organized as follows.

Section 2 provides the details of the configuration of the job shop production system considered in the present study. In Section 3, the salient aspects of the simulation model developed are described. This section also includes the description of the scheduling rules. Section 4 presents the details of the experimentation. The results and analysis are provided in Section 5. Conclusions are presented in Section 6.

2. Job shop system configuration

A realistic job shop system configuration has been developed for investigation in the present study. This configuration has been determined based on the configuration of job shops considered by various researchers [22]. Most of the studies have used between four and 10 machines. Hence, in the present study, a job shop system consisting of eight machines is chosen. The machines are not identical and perform different operations. However, each machine can process different types of jobs by changing the setup. The characteristics of the job shop system considered for investigation in the present simulation study are provided in following subsections.

2.1. *Assumptions made in the present study*

The present study focuses on scheduling a dynamic job shop under the following assumptions.

(1) There is only one machine of each type in the shop.
(2) Each machine can perform only one operation at a time on any job.
(3) An operation of a job can be performed by only one machine.
(4) Once an operation has begun on a machine, it must not be interrupted.
(5) An operation of a job cannot be performed until its preceding operations are completed.
(6) There are no alternate routings, i.e., an operation of a job can be performed by only one type of machine.
(7) The setup times of jobs on machines are sequence dependent and are known.
(8) Each machine is continuously available for production, i.e., no machine breakdowns.
(9) There is no restriction on queue length at any machine.

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2.2. Job data

The shop processes 10 types of jobs. Each of the 10 job types has an equal probability to be assigned to an arriving job. The same type of jobs can be processed with the same setting of the machine. However, the jobs may differ in terms of processing requirements, routing and number of operations. Each job consists of a set of operations to be performed on the machines in the shop. The number of operations for each job is uniformly distributed in the range 5–8. The routing of a job through the machines is determined by random assignment. The routing is established in such a manner that a machine is included in the routing not more than once. Processing times for operations are generated from an exponential distribution with a mean of 30 min.

2.3. Setup time

The setup time for jobs on the various machines is generated as follows. A separate setup time matrix is used for each machine in the shop. The mean setup time in the matrix is obtained by fixing the proportion of mean setup time to mean processing time (i.e., setup time ratio, s) at 30% in the base case of simulation experiments [21]. Using the mean setup times obtained above, the individual values of the setup times are generated from an exponential distribution. In the simulation experiments, the setup time ratio has also been fixed at 20% and 40% to study the effect of changing setup times.

2.4. Arrival time

It has been observed in the literature that in job shops, the distribution of the job arrival process closely follows the Poisson distribution [23]. Hence, the time between arrivals of jobs is exponentially distributed. The mean of this exponential distribution is determined for a specified shop utilization percentage and the processing requirements of the jobs. Thus, the mean interarrival time of jobs is obtained using the following relationship:

$$a = \frac{\mu_p \mu_g}{Um}, \qquad (1)$$

where a is the mean interarrival time, μ_p the mean processing time per operation, μ_g the mean number of operations per job, U the shop utilization and m the number of machines in the shop.

In the present study, $\mu_p = 30$, $\mu_g = 6.5$, $m = 8$. In the base case of simulation experiments U is set equal to 0.90. Simulation experiments have also been carried out for $U = 0.87$.

2.5. Due date of jobs

In job shop scheduling, the total work content (TWK) method has been used widely for due date assignment [23]. Using TWK method, the due date of each job is set equal to the sum of the job arrival time and a multiple of the total job processing time. Thus, the due date of a job is determined using the following equation.

$$d_i = a_i + k(p_i + n_i \mu_s), \qquad (2)$$

where d_i is the due date of job i, a_i the arrival time of job i, k the due date tightness factor, p_i the total processing time of job i, n_i the number of operations of job i and μ_s the mean setup time of an operation.

In the base case of simulation experiments, the value of k is set equal to 5. Simulation experiments have also been carried out for two other values of k (i.e., $k = 3$ and 7).

3. Development of simulation model

In the present study, a discrete event simulation model is developed for the operation of the job shop production system. The simulation model is developed using the C programming language and run on a PC with Pentium processor.

Generally, a discrete event simulation model of a system is constructed by defining the events that can occur and then modeling the logic associated with each event to capture the changing status in the system. Executing the logic associated with each event in a time-ordered sequence produces a simulation of the system.

A schematic flow chart of the logic of the simulation model is shown in Fig. 1.

The discrete event model views the job shop system as consisting of entities, their associated attributes and files which contain entities with common characteristics. The entities in the job shop are jobs and machines. The operation of the job shop is conceptualized as a succession of events centering on the jobs to be processed.

3.1. Structure of the simulation model

The simulation model is structured in a modular way consisting of a number of modules, each performing a specific role. The modules included in the simulation model are as follows:

(1) initialization module,
(2) job data generation module,
(3) timing module,
(4) event routine module,
(5) random sample generation module,
(6) file processing module,
(7) job scheduling module,
(8) report generation module.

A brief description of the modules such as event routine, job scheduling and report generation is presented in the following subsections.

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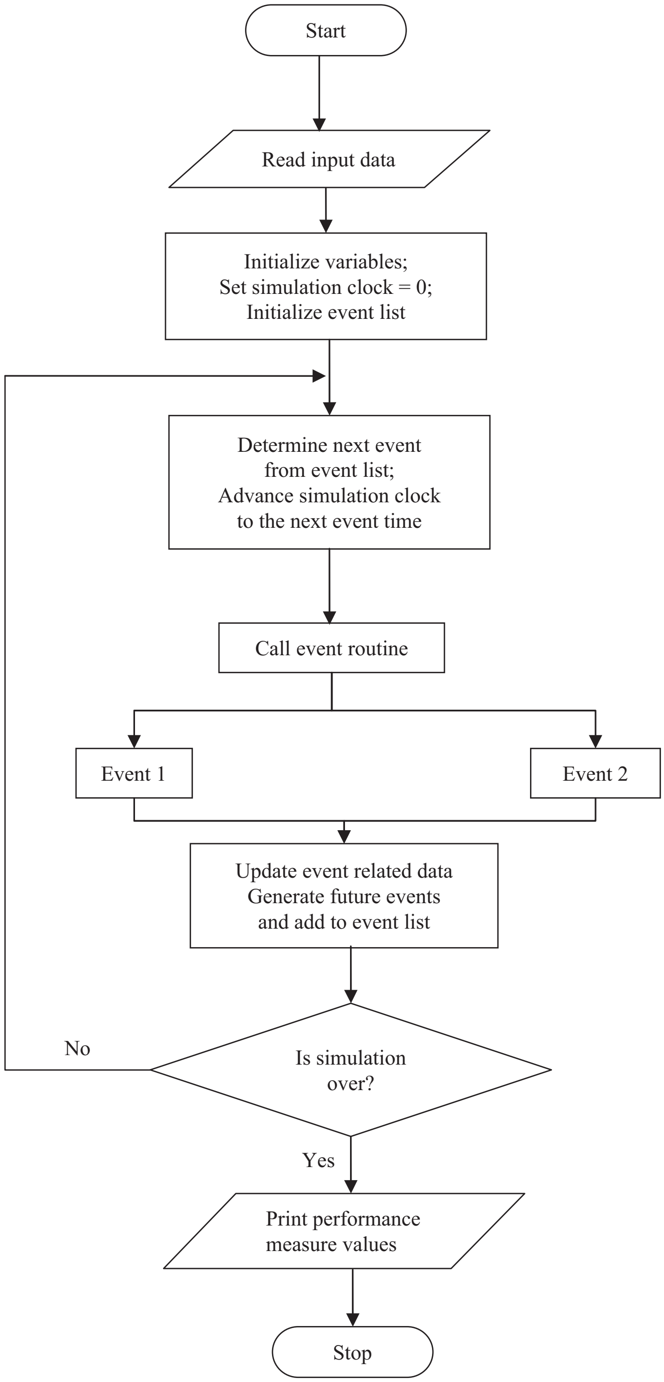

Fig. 1. Flow chart of simulation logic.

3.1.1. Event routine module

This module contains the subroutines, which deal with the following events that characterize the operation of the system.

(1) Arrival of a job to the shop.
(2) Departure of a job from a machine.

3.1.2. Job scheduling module

This module contains subroutines to deal with the scheduling of jobs on machines using various scheduling rules. Using a scheduling rule, for each of the machines, the jobs to be processed are scheduled as follows [3]. When a machine becomes free, it has to be decided which of the waiting jobs (if there is any in the queue of the machine) is to be processed on the machine. For making this decision, a scheduling rule is used to assign to each of the waiting jobs, a priority value. The job having the highest priority, which is defined by either the smallest or the largest priority value is selected for processing next. In the present study, seven existing rules from the literature are used. Five new scheduling rules for the sequence-dependent setup time environment of the job shop operation have also been proposed in the present study.

The following notations are used for the description of the scheduling rules:

m: index of the machine for which the job to be processed next has to be selected;
t: time at which the priority values are calculated;
i: index of the job for which the priority values are calculated;
j: index of the operation of job i;
k_i: set of operations to be performed on machines according to the routing of job i;
r_i^m: arrival time of job; i at machine m;
N_m^t: set of jobs waiting for processing in the queue of machine m at time t;
s_{ij}^m: setup time of operation j of job i on machine m;
p_{ij}^m: processing time of operation j of job i on machine m;
d_i: due date of job i;
Z_i^t: priority value of job i at time t.

The Scheduling rules are described as follows:
Existing rules:

(1) FIFO: First In First Out.
$Z_i^t = r_i^m$ where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_t^m\}$. Using the FIFO rule, the jobs are processed in the order they arrive at the machine.
(2) SPT: Shortest Processing Time.
$Z_i^t = p_{ij}^m$ where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the shortest processing time for the imminent operation is selected.
(3) EDD: Earliest Due Date.
$Z_i^t = d_i$ where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the smallest due date is selected.
(4) EMDD: Earliest Modified Due Date [4].
$Z_i^t = \max\{0, d_i - t - \sum_{q=j}^{Ki} piq\}$, where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the smallest modified due date is selected.
(5) CR: Critical Ratio.
$Z_i^t = (d_i - t)/\sum_{q=j}^{Ki} piq$, where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the smallest critical ratio is selected.

(6) SIMSET: SIMilar SETup [15].
$Z_i^t = s_{ij}^m$, where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the smallest setup time is selected.
(7) JCR: Job with similar setup and Critical Ratio [15].

Select a job identical to the job that just finishes processing on the machine. When there is no identical job, select a job with the smallest critical ratio.

The following are the new setup-oriented scheduling rules proposed in the present study:

(1) SSPT: Shortest (Setup time + Processing Time).
$Z_i^t = p_{ij}^m + s_{ij}^m$, where the highest priority is given to the job i^* with $Z_{i*}^t = \min\{Z_i^t | i \in N_m^t\}$, i.e., the job with the smallest value of the sum of setup time and processing time is selected.
(2) JSPT: Job with similar setup and Shortest Processing Time.
Select a job identical to the job that just finishes processing on the machine.
When there is no identical job, select a job with the smallest processing time for the imminent operation.
(3) JEDD: Job with similar setup and Earliest Due Date.
Select a job identical to the job that just finishes processing on the machine. When there is no identical job, select a job with the earliest due date.
(4) JEMDD: Job with similar setup and Earliest Modified Due Date.
Select a job identical to the job that just finishes processing on the machine. When there is no identical job, select a job with the earliest modified due date.
(5) JSSPT: Job with similar setup and Shortest (Setup time + Processing Time).

Select a job identical to the job that just finishes processing on the machine. When there is no identical job, select a job with the smallest value of the sum of setup time and processing time for the imminent operation.

3.1.3. Report generation module

This module performs the task of consolidating the output of the simulation model to present results for the performance measures such as mean flow time, mean tardiness, mean setup time and mean number of setups. These performance measures are described as follows:

(1) mean flow time, F: it is the average time a job spends in the shop

$$F = [1/n]\left[\sum_{i=1}^{n} F_i\right];$$

(2) mean tardiness, T: it is the average tardiness of a job

$$T = [1/n]\left[\sum_{i=1}^{n} Ti\right];$$

(3) mean setup time: it is the average time spent by a job for the setup;
(4) mean number of setups: it is the average number of setups encountered by a job during its processing through various machines in the shop;

where C_i is the completion time of job i; a_i the arrival time of job i; d_i the due date of job i; n the number of jobs completed during the time interval from steady state period to simulation ending time; F_i the flow time of job i; $F_i = C_i – a_i$; T_i the tardiness of job i; $T_i = \max\ \{0, L_i\}$ (L_i = lateness of job i; $L_i = C_i – d_i$).

These performance measures are determined using the simulation output after the shop reaches steady state. Welch's method described by Law and Kelton [24] is used for identifying the steady state. The simulation output corresponding to the initial transient period is not considered for the computation of performance measures.

3.2. Verification and validation of the simulation model

Since the present study involves a conceptual job shop system, a multi-level verification exercise was performed to ensure correct programming and implementation of the conceptual model using the following steps.

(a) Debugging the program.
(b) Checking the internal logic of the modules of the model.
(c) Comparing the model output with the information obtained from a manual simulation using the same data.
(d) Running the model under different settings of the input parameters and checking whether the model behaves in a plausible manner.

4. Experimentation

Using the simulation model as an engine for experimentation, a number of experiments have been conducted. The objective of the experimentation is to investigate the performance of scheduling rules in a job shop system when setup times are sequence dependent. The details of experimentation are provided in the following sections.

4.1. Identification of steady state

The first stage in the simulation experimentation is determining the end of the initial transient period (identification of the steady state). For this purpose, Welch's procedure described in Law and Kelton [24] is

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used. It is a graphical procedure consisting of plotting moving averages for the output performance measures. The end of the initial transient period is the time at which the moving averages approach a level value. For this purpose, a pilot simulation study was conducted in the present study. Ten replications were made. Each replication simulated the operation of the system for the completion of 1000 jobs. The experimental setting used was as follows. Mean interarrival time of jobs: 27 min; due date tightness factor: 5; ratio of mean setup time to mean processing time: 30%; scheduling rule: FIFO. The performance measures such as mean flow time, mean tardiness, mean number of setups and mean setup time were determined. It was found that the moving averages for all the performance measures approached a level value when 250 jobs were completed.

4.2. Identifying different scenarios for analysis

In the present simulation study, the first experimentation (scenario 1) involves the following settings: Mean interarrival time of jobs, a: 27 min; due date tightness factor, k: 5; ratio of mean setup time to mean processing time, s: 30%; scheduling rules: seven scheduling rules from the literature and five new setup-oriented scheduling rules described in Section 3.1.6. The performance of scheduling rules has also been investigated for three other scenarios. The experimental settings for all the four scenarios are summarized in Table 1.

Ten replications are performed for each experimental setting. The simulation for each replication is run for 1250 job completions. Jobs are numbered on arrival at the system and the simulation output from jobs numbering 1–250 is discarded. The outputs for the remaining 1000 jobs (jobs numbering 251–1250) are used for the computation of the performance measures.

5. Results and discussion

For each scenario the simulation results are subjected to statistical analysis using the analysis of variance (ANOVA) procedure in order to study the effect of experimental factors on the performance measures.

In scenario 1, the scheduling rule is the only factor and hence, one-way ANOVA has been carried out. For scenarios 2–4, two-factor ANOVA method is adopted. In performing statistical analysis, the simulation results pertaining to each replication have been accommodated in each treatment combination (cell). ANOVA-F test has been carried out to determine whether the treatment means are significantly different from each other. The least significant difference (LSD) method was used for performing pairwise comparisons in order to determine the means that differ from other means. The null hypothesis (H_0) is that all means are equal. The alternate hypothesis (H_1) is that at least two means are significantly different. All the tests were conducted at 5% level of significance. Values that are not significantly different are grouped. The results obtained and their analyses are presented in the following sections.

5.1. Results and discussion for scenario 1

Scenario 1 represents the base case wherein the purpose of analysis is to investigate the performance of scheduling rules in sequence-dependent job shop environment. At first, the average values of the performance measures are analyzed. Then, statistical analysis using ANOVA and means test are presented.

5.1.1. Analysis of means

The experimental settings for the scenario 1 are as follows: mean interarrival time of jobs, $a = 27$ min, due date tightness factor, $k = 5$ and setup time ratio $s = 30\%$. For each of the 12 scheduling rules, the simulation output for the 10 replications is averaged. These average values are presented in Figs. 2–5.

5.1.1.1. Mean flow time. Fig. 2 shows the simulation results for the mean flow time measure when different scheduling rules are used. It is found that SPT and SSPT rules provide smaller values for mean flow time. It is reported in the literature [21] that SIMSET performs best for mean flow time when the setup time of jobs are sequence dependent. But, the present study shows that SSPT is better then SIMSET for mean flow time.

Table 1
Experimental settings for the scenarios

Scenario	Experimental setting			Purpose of investigation
	Mean interarrival time	Setup time ratio (%)	Due date tightness factor	
1	27	30	5	Base case—analyze the performance of scheduling rules
2	27	20, 30, 40	5	Analyze the effect of changing setup time ratio
3	27	30	3, 5, 7	Analyze the effect of due date tightness factor
4	27, 28	30	5	Analyze the effect of changing shop load (i.e., changing mean interarrival time of jobs)

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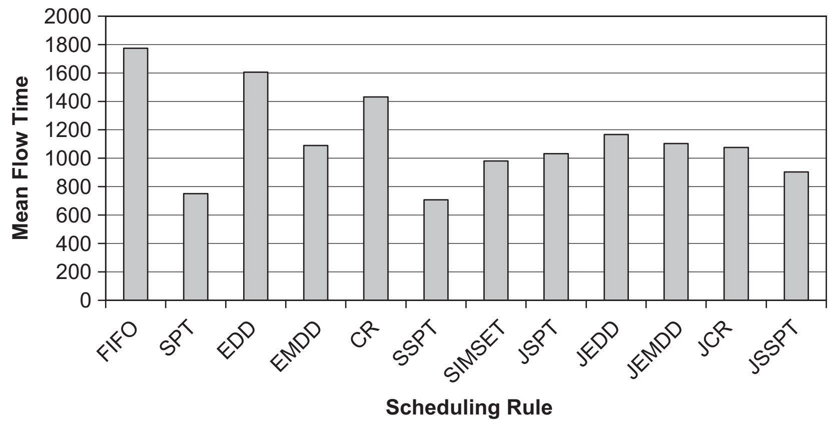

Fig. 2. Mean flow time ($k = 5$, $s = 30\%$).

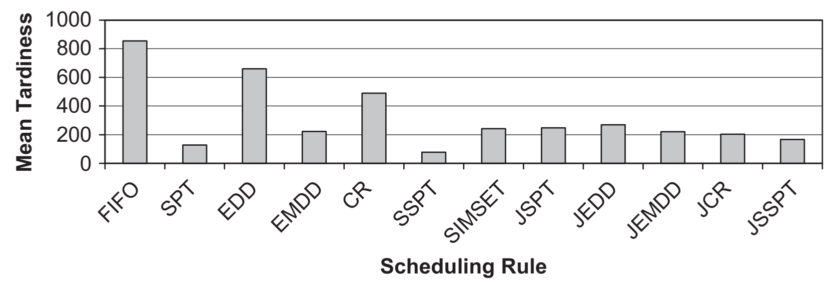

Fig. 3. Mean tardiness ($k = 5$, $s = 30\%$).

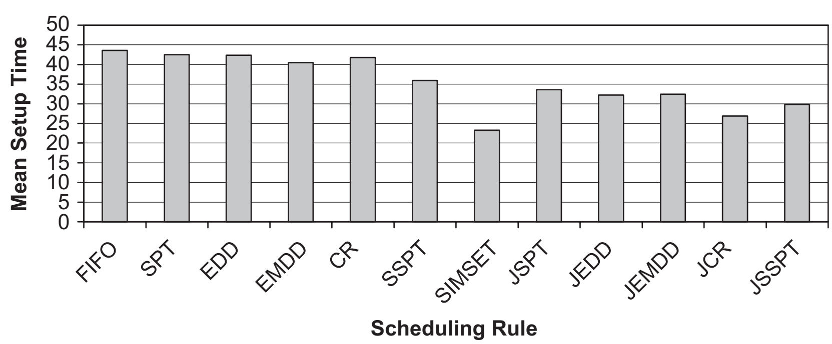

Fig. 4. Mean setup time ($k = 5$, $s = 30\%$).

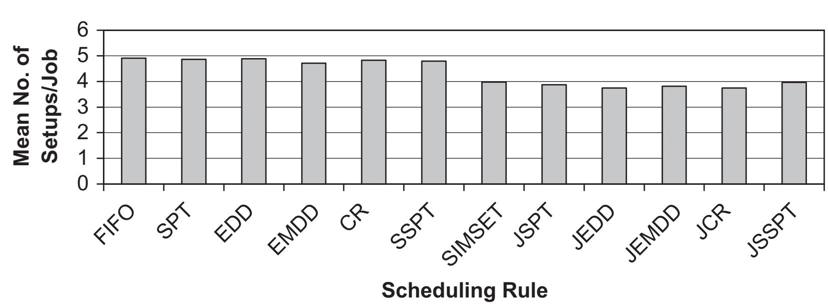

Fig. 5. Mean number of setups/job ($k = 5$, $s = 30\%$).

It can be observed that the setup-oriented rules such as JEDD, JEMDD and JCR perform better than ordinary rules such as EDD, EMDD and CR. Also, the modified due date based rules (EMDD, JEMDD) perform better than their counter parts EDD, JEDD which do not update the due dates dynamically.

5.1.1.2. Mean tardiness. Mean tardiness is a due date related performance measure and hence it has implications on average customer delivery performance. The performance of various scheduling rules for the mean tardiness measure is shown in Fig. 3. The SSPT rule performs best. As observed for the mean flow time measure, it is found that the SSPT rule outperformed SIMSET for the mean tardiness measure also.

Among the due date based rules, JCR provides lower values for mean tardiness, since it makes use of the due date data in addition to setup time data.

5.1.1.3. Mean setup time. This measure is a setup related measure. It denotes the average time incurred for setup activities in processing a job. Fig. 4 depicts the performance of the scheduling rules for the mean setup time measure. It is found that SIMSET rule outperforms all other rules. The second best rule in many cases is JCR rule followed by JSSPT rule. As expected, the non-setup-oriented rules such as FIFO, SPT, EDD, EMDD and CR lead to higher values for mean setup time of a job.

5.1.1.4. Mean number of setups. Fig. 5 shows the results for the mean number of setups per job when different rules are used for the scheduling decision. It is found that JCR rule provides smallest value for mean number of setups per job. Setup-oriented rules such as SIMSET, JSPT, JEDD, JEMDD, JCR and JSSPT rules perform better than non-setup-oriented rules.

5.1.2. ANOVA results

Using simulation results for 10 replications, ANOVA-*F* test has been carried out for each performance measure to determine whether the means are significantly different from each other. These results are shown in Table 2 for the performance measures such as mean flow time, mean tardiness, mean setup time, and mean number of setups. In all cases, since the *P*-value of the *F*-test is less than 0.05, there is a statistically significant difference between the mean performance measures from one scheduling rule to another at the 95% confidence level. To determine the means that are significantly different from other means, the LSD method of multiple comparison test is used. The results obtained using the LSD test are shown in Table 3.

The LSD test groups the results into five significantly different groups labeled a, b, c, d, e for mean flow time, six groups labeled a, b, c, d, e, f for mean tardiness, eight groups labeled a, b, c, d, e, f, g, h for mean setup time and five groups

Table 2
ANOVA results for base case

Performance measure	Source of variation	Sum of squares	Mean square	*F*-ratio	*P*-value
Mean flow time	Between groups	6.18704E6	562458.0	24.22*	0.0000
	Within groups	2.50792E6	23221.5		
Mean tardiness	Between groups	5.97862E6	543511.0	33.96*	0.0000
	Within groups	1.72854E6	16005.0		
Mean setup time	Between groups	5073.11	461.191	158.27*	0.0000
	Within groups	314.698	2.91387		
Mean number setups/job	Between groups	29.6142	2.6922	119.25*	0.0000
	Within groups	2.43829	0.0225768		

*Denotes *f* ratios significant at 5% significance level.

Table 3
Results for multiple regression base case (scenario 1)

Scheduling rule	Mean flow time	Mean tardiness	Mean setup time	Mean number of setups
FIFO	1372.610[e]	855.792[f]	43.5942[h]	4.90731[e]
SPT	613.379[a]	128.315[a,b]	42.5244[g,h]	4.86445[e]
EDD	1281.990[d,e]	659.333[e]	42.3745[g,h]	4.88306[e]
EMDD	1017.780[e]	223.063[b,c]	40.464[f]	4.71229[d]
CR	1208.380[d]	489.325[d]	41.8205[f,g]	4.8289[d,e]
SSPT	597.756[a]	76.4587[a]	35.9372[e]	4.79169[d,e]
SIMSET	919.306[b,c]	241.362[c]	23.2358[a]	3.97076[c]
JSPT	905.452[b,c]	247.457[c]	33.6076[d]	3.87475[b,c]
JEDD	1002.170[c]	268.115[c]	32.219[d]	3.74585[a,b]
JEMDD	954.406[e]	219.662[b,c]	32.3929[d]	3.81382[a,b]
JCR	1007.170[c]	202.155[b,c]	26.9052[b]	3.73854[a]
JSSPT	811.125[b]	165.866[a,b,c]	29.8227[c]	3.96113[c]

For each performance measure, values with the same letter are not found significantly different from each other by statistical test.

Table 4
ANOVA results for two-way analysis for scenario 2

Source of variation	*F*-ratio for performance measures			
	Mean flow time	Mean tardiness	Mean setup time	Mean number of setups/job
Main effects				
A: scheduling rule	130.75*	91.94*	359.07*	340.42*
B: setup time ratio	130.58*	108.32*	4030.68*	34.63*
Interaction AB	4.56*	7.31*	21.29*	1.02*

*Denotes *f* ratios significant at 5% significance level.

labeled a, b, c, d, e for mean number of setups. For the mean flow time measure, SSPT and SPT rules form a unique group labeled 'a'. Though there is no statistically significant difference among SSPT, SPT and JSSPT rules for the mean tardiness measures, SSPT rule provides the smallest value. The SIMSET rule forms a unique group labeled 'a' that denotes its superior performance for the mean setup time measure. The setup-oriented rules such as JCR, JEDD and JEMDD provide smaller values for mean number of setups.

5.2. Results and analysis for scenario 2

In this scenario, three different setup time matrices for each of the eight machines in the shop are used to investigate how the system performance is affected when the ratio of mean setup time to mean processing time changes. Simulation results are obtained for the two-factor experiments wherein the 12 scheduling rules form the first factor and the three levels of setup time ratio ($s = 20\%$, 30% and 40%) form the second factor. Ten replications are made for each of the 36 simulation experiments arising out of the combination of 12 scheduling rules and three setup time ratios. The results of two-factor ANOVA are shown in Table 4.

The main effects (scheduling rule, setup time) are significant for all the performance measures. The interaction effects are significant for the measures such as mean flow time, mean tardiness and mean setup time. The interaction plots are obtained for all the measures. However, due to space limitations, the plots for mean flow time and mean tardiness are shown in Figs. 6 and 7, respectively.

As evident from these figures, there is an increase in the performance measure values when the setup time ratio is increased. However, it is found that the rate of increase is smaller for the setup-oriented rules when compared to ordinary rules. The proposed rule, SSPT performs better than SPT rule for the measures such as mean flow time and mean tardiness when the setup time is fixed at 30% or 40%.

5.3. Results and analysis for scenario 3

The total work content method has been used in the present study for setting the due dates of jobs. The due date of each job is set equal to the sum of the arrival time and a multiple (due date factor, k) of the total processing time. In the base case (scenario 1), the due date factor is set equal to 5. In order to investigate the effect of due date tightness, the due date factor has been set at 3 and 7 to represent tight and loose due dates, respectively. Simulation experiments are conducted using a two-factor full factorial design. The experimental factors are job-scheduling rules (12 rules) and

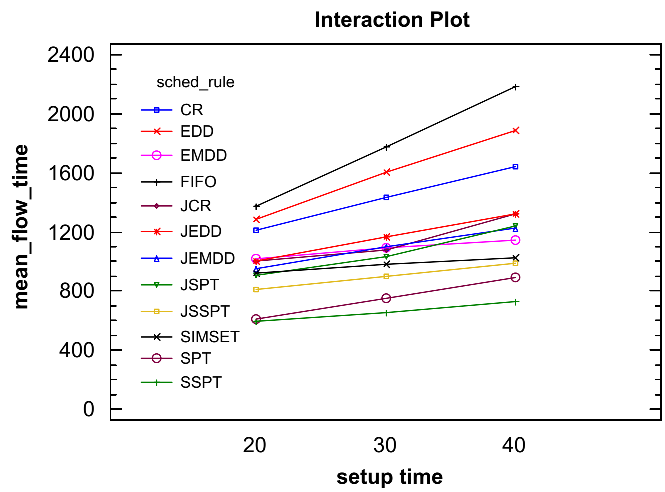

Fig. 6. Interaction plot for scenario 2—mean flow time.

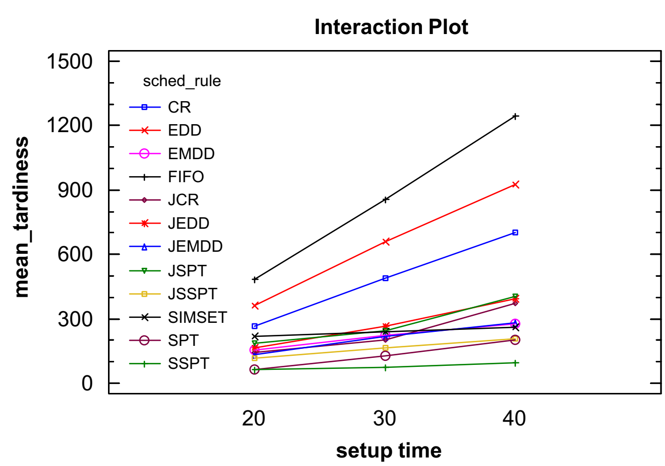

Fig. 7. Interaction plot for scenario 2—mean tardiness.

Table 5
ANOVA results for two-way analysis for scenario 3

Source of variation	F-ratio for performance measures			
	Mean flow time	Mean tardiness	Mean setup time	Mean number of setups/job
Main effects				
A: scheduling rule	160.01*	105.33*	534.56*	401.84*
B: due date factor	0.95	338.95*	0.07	0.02
Interaction AB	1.21	6.79*	0.18	0.33

*Denotes *f* ratios significant at 5% significance level.

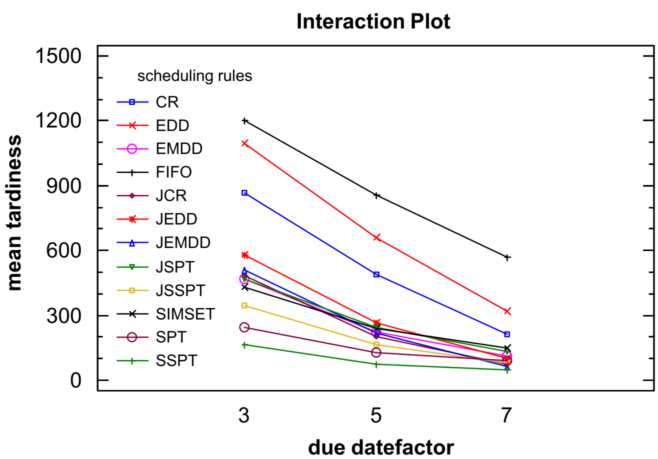

Fig. 8. Interaction plot for scenario 3—mean tardiness.

due date tightness (three levels, i.e., $k = 3,5,7$). Ten replications are made for each of the 36 (12 scheduling rules × 3 due date tightness levels) simulation experiments. The results of the two-factor ANOVA are shown in Table 5.

The main effect of the scheduling rules is statistically significant for all the performance measures. As expected, due date tightness significantly affects mean tardiness measure only. Further, the interaction effect is also significant for mean tardiness. Fig. 8 shows the interaction plot for mean tardiness.

It is evident that SSPT rule provides consistently best performance for all the three levels of the due date tightness. SPT rule ranks second. The setup-oriented rules such as JCR, JEDD, JEMDD, JSPT, JSSPT and SIMSET provide similar performance under medium due date tightness. However, there is difference in performance among these rules when the due dates are tight or loose.

5.4. Results and analysis for scenario 4

In this scenario, two different mean interarrival times of jobs are considered to represent the working of the shop under two different shop loads. The mean interarrival times chosen are $a = 27$, 28 corresponding to the expected system utilization of 90% and 87%, respectively. Two-factor simulation experiments are conducted with the 12 scheduling rules constituting the first factor and the two mean interarrival time forming the second factor. Ten replications are made for each of the 24 simulation experiments arising out of the combination of 12 scheduling rules and the two mean interarrival times. The two-factor ANOVA results are presented in Table 6.

The main effects of the scheduling rule and arrival time are significant for all the performance measures. The interaction effects are not significant for any of the performance measures. The means of the 10 replications for the 24 experiments are shown in Figs. 9 and 10 for the performance measures such as mean flow time and mean tardiness, respectively. Similar figures were obtained for mean setup time and the mean number of setups also; but not provided here due to space limitations.

As shown in Figs. 9 and 10, when the shop load is high (mean interarrival time is 27 min), mean flow time and mean tardiness values are also higher. At high load conditions, jobs wait longer for processing at various machine queues and hence the increase in these two performance measures. It is also found that the pattern of variation for each scheduling rule for the two cases of mean interarrival time of jobs is same.

The plot obtained for mean setup time (not included here due to space limitations) shows that the values of mean setup time per job are almost same for the ordinary rules in both cases of mean interarrival time. However, for the setup-oriented rules, the mean setup time per job is found to be slightly more for case 1 (case 1 corresponds to the mean interarrival time of 28 min) compared to that of case 2 (case 2 corresponds to the mean interarrival time of 27). The shop load is lesser for case 1, since the arrival rate of jobs is less. Hence, there will be less number of similar jobs at any time. This leads to higher values for mean setup time per job for setup-oriented rules in case 2. It can be noted that a similar pattern of variation in performance as described above is observed for number of setups per job for cases 1 and 2.

5.5. Desirable operational policies

Based on the discussion of results presented in the preceding subsections, the scheduling rules that perform best for various performance criteria are shown in Table 7.

For the performance measures such as mean flow time and mean tardiness, the SSPT rule proposed in the present

Table 6
ANOVA results for two-way analysis for scenario 4

Source of variation	*F*-ratio for performance measures			
	Mean flow time	Mean tardiness	Mean setup time	Mean number of setups/job
Main effects				
A: scheduling rule	85.11*	55.96*	288.06*	241.92*
B: mean interarrival time	21.27	17.39*	19.83*	8.11*
Interactions AB	0.55	0.65	4.80*	0.24

*Denotes *f* ratios significant at 5% significance level

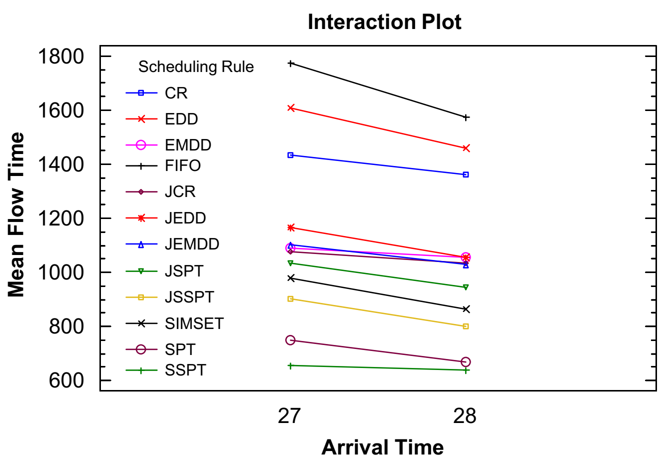

Fig. 9. Interaction plot for scenario 4—mean flow time.

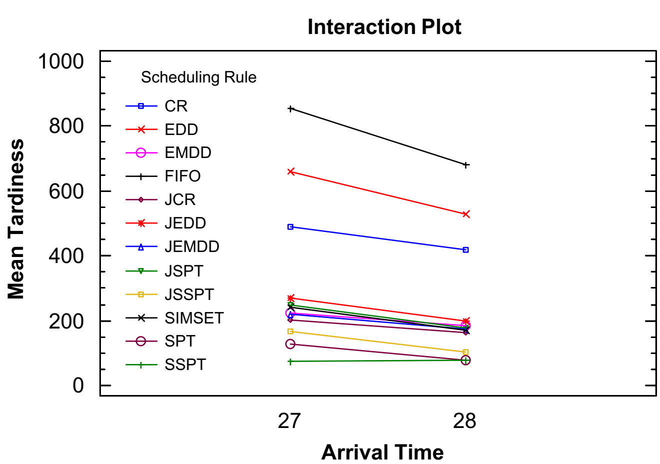

Fig. 10. Interaction plot for scenario 4—mean tardiness.

work performs better in large number of experiments under both the shop load conditions. SIMSET rule outperforms all other rules for the mean setup time measure for both the shop load conditions. The setup-oriented rule JCR performs better for the mean number of setups in large number of experiments under both the conditions of shop loading.

Table 7
Desirable operational policies

Performance measure	Scheduling rule[a]	
	Case 1 (shop load: 90%)	Case 2 (shop load: 87%)
Mean flow time	SSPT (6) SPT (3)	SSPT (6) SPT (3)
Mean tardiness	SSPT (7) SPT (1) JEDD (1)	SSPT (4) SPT (3) JCR (1) JEMDD (1)
Mean setup time	SIMSET (9)	SIMSET (9)
Mean number of setups/job	JCR (7) JEDD (1) JEMDD (1)	JCR (6) JEMDD (2) JEDD (1)

[a]Numbers in brackets denote the number of times the specified rule provides best performance in nine experiments (3 due date factors × 3 setup time ratios).

5.6. Development of metamodel

A metamodel is a simplified analytical model, which is derived using the results obtained from a simulation model [25]. When such an auxiliary model is developed, further investigation of the real-world system using this model is simpler and less costly than conducting additional simulation experiments.

The simulation results obtained for scenario 2 are used to develop regression-based metamodels. The linear regression concept proposed by Kleijnen [26] is used for this purpose. In the present study, the scheduling rules and the setup time ratios are the independent variables. From the desirable operational policies presented in the preceding section, it is found that the scheduling rules such as SSPT, SPT and JCR provide better performance. Hence, these scheduling rules are considered for developing metamodels.

The performance measures are the dependent variables. Scheduling rules such as SSPT, SPT and JCR are considered for developing metamodels. Since the scheduling rules are qualitative in nature, they are represented by indicator or dummy variables. According to Montgomery and Peck [27], a qualitative variable (factor) with '*m*' level is represented by '*m*−1' indicator or dummy variables for formulating metamodel. Hence, the three scheduling rules are modeled by two-indicator variables x_1 and x_2. These variables take values 0 or 1 as defined below.

x_1	x_2	
0	1	If the observation is from SSPT rule
1	0	If the observation is from SPT rule
1	1	If the observation is from JCR rule

The setup time ratio is a quantitative variable and it is modeled by the variable $x3$. Significant interactions between scheduling rule and setup time ratio have been observed as described in Section 5.2. Hence, the cross product terms involving the indicator variables and the quantitative variables are also defined to represent the interaction effects. Taking these into consideration, the metamodel has been formulated as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x3 + \beta_5 x_2 x_3 + e, \quad (3)$$

where Y is the performance measure; β_0 the constant or intercept; β_1, β_2 the coefficients corresponding to the main effect of scheduling rules; β_3 the coefficients corresponding to the main effect of setup time ratios; β_4, β_5 the coefficients corresponding to the interaction effect of scheduling rules and setup time ratios; e the error.

There are nine simulation experiments arising out of the combinations of scheduling rules and setup time ratios (3 scheduling rules × 3 setup time ratios). For each combination, simulation results are available for each of the five performance measures (simulation results from scenario 2). Multiple linear regression analysis has been carried out using the simulation results for getting a set of five metamodels, one corresponding to each performance measure based on Eq. (3). The ANOVA results for the metamodels are shown in Table 8.

5.6.1. Results and discussion

Table 8 provides the ANOVA results for the metamodels. The explanatory power of the metamodels can be inferred from the value of the coefficient of determination R^2 obtained from the ANOVA for the whole model. This analysis also provides the P-value (probability value) for the model, from which the significance of the postulated metamodel can be known. Multiple linear regression analysis of the simulation results provides the estimates of the regression coefficients of the independent variables in the metamodels. The following observations are made:

(1) The coefficient of determination R^2 for the metamodels for the five performance measures has a high value. Hence, a larger proportion of the variation in the performance measures is explained by independent variables, namely the scheduling rules and the setup time ratios.
(2) The regression metamodels are also found to be highly significant since the P-value (0.0000) is less than the significance level, 0.05.
(3) The coefficient of determination R^2 and the adjusted R^2 values are very close implying that the model has not been over specified by including terms that do not contribute meaningfully to the fit.
(4) The adequacy of the models has been verified using the residual plots. Plots of the residual values versus the corresponding fitted values were made. These plots were found to be having no patterns, implying that there are no obvious model defects.
(5) Similar inferences have been made by plotting the residual values against the corresponding values of the independent variables and by plotting the residual values on the normal probability paper.

These inferences reveal that the metamodels developed adequately model the simulation model and thus can be of considerable interest for further application.

The metamodels obtained using the estimates of regression coefficients are as follows:

$$\text{mean flow time} = 466.6330 - 132.6820x_1 + 192.2190x_2 + 647.5970x_3 + 746.5180x_1x_3 + 942.0750x_2x_3, \quad (4)$$

$$\text{mean tardiness} = 36.4485 - 111.3120x_1 - 141.8670x_2 + 142.5250x_3 + 543.8900x_1x_3 + 1008.6000x_2x_3, \quad (5)$$

Table 8
Results of analysis of variance for the metamodels

Performance measure	Source of variation	Sum of squares	Mean squares	F-ratio	P-value	Coefficient of determination R^2	Adjusted R^2
Mean flow time	Model	4.7873E6	957459.0	71.84*	0.0000	81.0471	79.9189
	Error	1.11951E6	13327.5				
Mean tardiness	Model	7666990.0	153398.0	18.36*	0.0000	82.212	81.3674
	Error	702003.0	8357.18				
Mean setup time	Model	9715.82	1943.16	438.90*	0.0000	96.3134	96.0939
	Error	371.896	4.42733				
Mean number of setups/job	Model	24.762	4.95241	331.41*	0.0000	95.1753	94.8881
	Error	1.25526	0.0149435				

*Denotes f ratios significant at 5% significance level.

$$\text{mean setup time} = 5.6839 - 4.0929x_1 - 4.7249x_2 + 99.8487x_3 + 35.5280x_1x_3 - 2.2044x_2x_3, \tag{6}$$

$$\text{mean number of setups} = 4.9733 + 0.0905x_1 - 0.8511x_2 - 0.6179x_3 - 0.0532x_1x_3 - 0.7027x_2x_3. \tag{7}$$

5.6.2. Validation of metamodels

In order to test the validity of the metamodels developed input values for the independent variables that fall within the domain of definition of Eqs. (4)–(7) are used. For example the setup time ratio, s is fixed at 0.20.0.30 and 0.40 for constructing the metamodels denoted by Eqs. (4)–(7). Different values of setup time ratio in the interval 0.2–0.4 are chosen and used as inputs to the simulation model when the three scheduling rules are used. The performance

Table 9
Validation results of the metamodels

Scheduling rule	Performance measure	Setup time ratio (%)	Simulation results	Metamodel results	Error deviation (%)
SSPT	Mean flow time	24	618.443	622.06	−0.005
		28	611.6263	647.96	−0.032
		32	669.4373	673.86	−0.006
		36	680.3753	699.79	−0.028
	Mean tardiness	24	73.59988	70.65	0.040
		28	73.08341	76.36	−0.044
		32	84.86926	82.06	0.033
		36	84.3331	87.76	−0.040
	Mean setup time	24	30.23413	29.65	0.019
		28	34.51634	33.64	0.025
		32	38.44943	37.64	0.021
		36	42.30409	41.63	0.015
	Mean number of setups	24	4.878553	4.83	0.009
		28	4.842377	4.80	0.008
		32	4.811	4.78	0.006
		36	4.802141	4.75	0.010
SPT	Mean flow time	24	640.414	668.54	−0.043
		28	689.4014	724.30	−0.050
		32	766.7513	780.07	−0.017
		36	815.66	835.83	−0.025
	Mean tardiness	24	85.64193	89.88	−0.049
		28	113.77989	117.33	−0.031
		32	138.71716	144.78	−0.043
		36	165.3017	172.25	−0.042
	Mean setup time	24	34.00399	34.08	−0.002
		28	39.27447	39.50	−0.005
		32	45.88813	44.91	0.021
		36	51.14744	50.33	0.015
	Mean number of setups	24	4.933924	4.90	0.006
		28	4.904024	4.88	0.004
		32	4.896272	4.85	0.009
		36	4.854559	4.82	0.007
JCR	Mean flow time	24	1052.597	1040.37	0.011
		28	1130.595	1103.96	0.023
		32	1171.223	1167.55	0.003
		36	1267.891	1231.14	0.028
	Mean tardiness	24	163.3351	170.85	−0.046
		28	208.2177	216.90	−0.041
		32	257.8589	262.94	−0.019
		36	295.6834	308.98	−0.044
	Mean setup time	24	25.10198	24.39	0.028
		28	29.33342	28.30	0.035
		32	33.53766	32.21	0.039
		36	37.90635	36.11	0.047
	Mean number of setups	24	4.396604	4.57	−0.039
		28	4.443079	4.51	−0.015
		32	4.361366	4.46	−0.022
		36	4.213295	4.40	−0.044

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measure values obtained using the simulation outputs are then compared with the predicted values of performance measures for these setup time ratios using the metamodels. The performance measure values obtained through simulation are the averages over 10 replications. These results are provided in Table 9.

It is evident that the percentage deviation of the predicted values from the simulation result is within 5%. Hence, the metamodels provide a good prediction of the performance of the job shop system in the domain of their definition.

6. Conclusion

This paper addresses the job shop scheduling problem in the sequence-dependent setup time environment. A discrete-event simulation model has been developed for a realistic job shop production system. The simulation model has been passed through multi-level verification and validation exercise. The simulation output has been suitably subjected to steady state analysis to ensure that further investigations are free from initial bias. The results indicate that sequence-dependent setup time has a significant impact on the shop performance. Different scenarios characterized by variations in setup time ratios, due date tightness and shop load are investigated. The results can be summarized as follows.

(1) The setup-oriented rules such as SSPT, JSPT, SIMSET, JEDD, JEMDD, JCR, and JSSPT provide better performance under various shop conditions than ordinary rules. The difference in performance between these two groups of rules increases with increase in shop load and setup time ratio.
(2) The proposed rule SSPT is found to be performing better for the mean flow time and mean tardiness measures.

Flow time measure is a very critical indicator of the lead time and it also provides important information that can be used for setting the due dates or due date allowances. Moreover, it is proportional to the work in process levels. Mean tardiness is related to customer service or customer delivery performance. Considering these aspects, practitioners need to employ scheduling rules that meet the mean flow time and mean tardiness criteria. The proposed rule SSPT fulfils this requirement.

For the top three promising rules such as SSPT, SPT and JCR, regression-based metamodels have been developed. These metamodels are found to offer a good prediction of the performance of job shop system within the domain of their definition.

The results presented in this paper should be interpreted with reference to the job shop system considered for the simulation study and the experimental conditions described. Hence, there is a need for further research to develop and test new scheduling rules under different job shop conditions. For example, the scheduling rules can be tested in a sequence-dependent environment with system disruptions such as breakdowns of machines. Realistic system constraints such as fixture, tooling, etc., can also be considered in simulation. Taguchi's Design of experiments method can be used for simulation experiments. Taguchi's method helps in reducing the number of experiments when experimentation of a system involves many factors and many levels for each factor. Orthogonal arrays can be used for obtaining the experimental design matrices. The results for the DJSSP can be applied in a flexible manufacturing system (FMS) or computer integrated manufacturing (CIM) environment with appropriate modifications. In the literature, the configuration of the FMS is considered as a network of computer numerically controlled machines with parts of many types moved about by a conveyer or wire-guided material handling system. The random FMS is the equivalent of dynamic job shop in conventional production. It is intended for flexible production in high-variety, low-volume situations. While the change over (setup) times between parts of the same family are minimal in an FMS, the change over (setup) times between different families can be quite significant. Because of its integrated nature, scheduling for an FMS requires additional consideration of material handling systems. These aspects provide promising areas for further research.

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