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A SIMULATION BASED LEARNING MEACHANISM FOR SCHEDULING SYSTEMS WITH CONTINUOUS CONTROL AND UPDATE STRUCTURE

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ABSTRACT

A simulation based learning mechanism is proposed in this study. The system learns in the manufacturing environment by constructing a learning tree and selects a dispatching rule from the tree for each scheduling period. The system utilizes the process control charts to monitor the performance of the learning tree which is automatically updated whenever necessary. Therefore, the system adapts itself for the changes in the manufacturing environment and works well over time. Extensive simulation experiments are conducted for the system parameters such as monitoring (MPL) and scheduling period lengths (SPL) on a job shop problem with objective of minimizing average tardiness. Simulation results show that the performance of the proposed system is considerably better than the simulation-based single-pass and multi-pass scheduling algorithms available in the literature.

1 INTRODUCTION

One of the main functions of production systems is scheduling of limited resources. Scheduling problems encountered are stochastic and dynamic in nature. Thus, dispatching rules are commonly used in practice. There are hundreds of such rules in the literature. The performance of these rules is usually tested by simulation. The results indicate that none of them is superior in every condition. Hence, the selection of appropriate rule/s is not a trivial task. Another result in the literature is that switching to the different rules (multi pass) yields better performance than using one rule (single pass) for the entire horizon.

In a single-pass, a set of candidate rules is simulated and the one with the best long-run performance is selected and used during the whole planning horizon. On the other hand, multi-pass algorithms evaluate all the candidate dispatching rules at each short scheduling period and the best performer is selected to be used in that interval. Thus, in the long run, this process results in a combination of different dispatching rules. One of the shortcomings of this approach is that it requires too much computer time to simulate the performance of each candidate dispatching rule. Also, the procedure depends on the assumption that we know the probability distribution functions and the parameters of the processing and arrival times. However, this may not be the case if the demand patterns in the market and/or product types change rapidly, which is the situation for high tech industries. Also, the processing times may change due to the machines' depreciation over time. Hence, the simulation models constructed to evaluate the performance of the rules might become invalid after some time.

There are various studies in the literature that employ iterative simulation and artificial intelligence (AI) concepts for these applications. These are Wu and Wysk (1988), Ishii and Talavage (1991), Tayanithi, Manivannan, and Banks (1993), Shaw, Park and Raman (1992). Cho and Wysk (1993), Jeong and Kim (1998), Pierreval and Mebarki (1997), Kutanoglu and Sabuncuoglu (2001), and Suwa and Fujii (2003).

In this research, we develop a system to select the right dispatching rule among a set of candidate rules. The proposed system utilizes the intelligent machine learning techniques from computer science (i.e., data mining) and the process control charts from the statistical quality control as well as simulation. The objective of our system is to learn about the characteristics of the manufacturing system by constructing a learning tree and then selecting a dispatching rule for a scheduling period from this tree on-line. Therefore, we reduce the extensive simulation experiments. Moreover, we use the control charts to monitor the actual performance of the learning tree. If these charts signal that the current learning tree begins to perform poorly, a new tree is constructed based on the recent information gathered from the manufacturing system via simulation. In this study, we also address to three important issues: how frequently should we update the dispatching and how frequently should we monitor the performance of the manufacturing system that operates under a particular rule and how should we decide to update or continue with this rule at these monitoring points?" Both of these questions are also important for the success of the proposed system.

The rest of the paper is organized as follows. In Section 2, we present the proposed system. We give experimental design and the results of simulation experiments in Section 3. Finally, we explain the concluding remarks along with the future research directions in Section 4.

2 PROPOSED SYSTEM: INTELLIGENT SCHEDULING

The goal of the proposed system is to select the best dispatching rule (DR) among Candidate Dispatching Rules (CDRs) for a particular scheduling period. The general structure is shown in Figure 1. In this structure, there are five main subroutines, called modules. They operate in harmony to achieve the goal of selecting the best performing dispatching rule for each scheduling period (time interval during which a selected DR is used to schedule jobs) throughout the planning horizon. The *database* provides necessary data for both the learning module and the simulation module. It holds the *instance data*, which is composed of a number of attributes and a class value where attributes take values of manufacturing conditions and class value corresponds to the DR selected for a specific condition, for the learning algorithm to generate the learning tree. The *realized scheduling period data*, which represents the actual events that occur in a specific scheduling period such as the processing times, interarrival times and system conditions at the beginning of the scheduling period, is also stored in the database for assessment of DRs via simulation. Note that, realized scheduling period data is composed of random number generator seed numbers when we are experimenting with our approach in a computerized environment rather than a real life manufacturing system.

The *Simulation module* is used to measure the performances of the candidate dispatching rules. The simulation module is invoked by the *process controller module* whenever necessary. The simulation module's outputs (instance data) are sent to the database. These results are then used by the *learning module* to generate the learning tree. The learning module is mainly composed of two parts: *learning module-1* (LM1) and *learning module-2* (LM2) (see Figure 2). LM1 contains the learning tree that is constructed by the learning algorithm in LM2. Its responsibility is to select a new DR from the existing learning tree based on the current values of the system state attributes. The on-line controller module provides the current values of these attributes to LM1 and requests a new DR. In response, LM1 recommends the best DR to the on-line controller (see Figure 2). LM2 contains the learning algorithm that is used to generate the learning tree in LM1. As seen in Figures 1 and 2, the algorithm is invoked by the process controller module and the necessary data (instance data) is retrieved from the D2 database. C4.5 algorithms (Quinlan 1993) are used to create the learning tree.

Whenever a scheduling decision is to be made according to the current scheduling strategy (e.g., hybrid approach), the learning tree selects a new dispatching rule and this decision is implemented by the *on-line controller module* (i.e., it employs the selected DR in actual manufacturing conditions). It also supplies the realized scheduling period data to the database and monitors the real system for new rule selection symptoms, the triggering events that are defined in the scheduling strategy to answer the question of "when-to-schedule". The *process controller module* monitors the performance of the learning tree. It takes its inputs

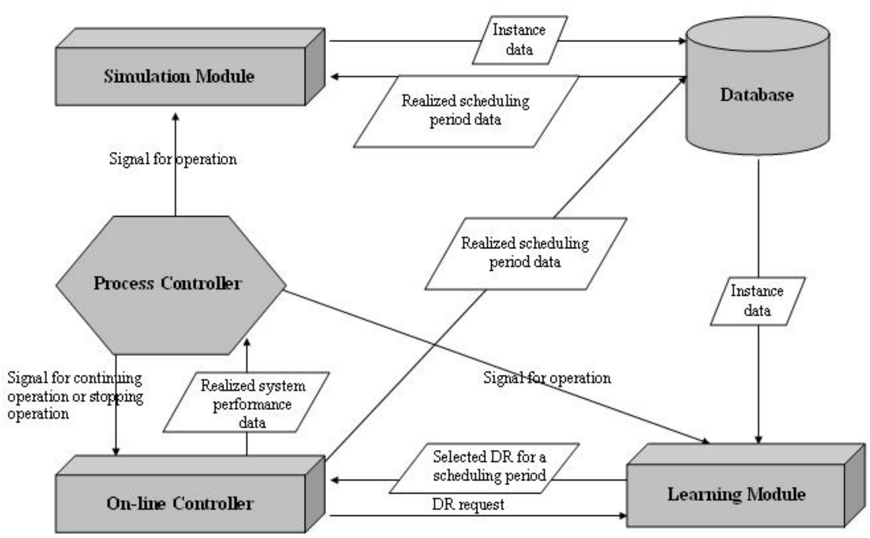


Figure 1: Proposed System - General Structure

(realized value of average tardiness) from the on-line controller module and monitors the performance of the learning tree. When the performance of the current learning tree is found to be insufficient, it requests from the simulation module to provide new training data (instance data) for the learning module and then sends a signal to the learning module to update the current learning tree with this new data set. As a result, new dispatching rules are selected from this updated learning tree and the process continues in this manner.

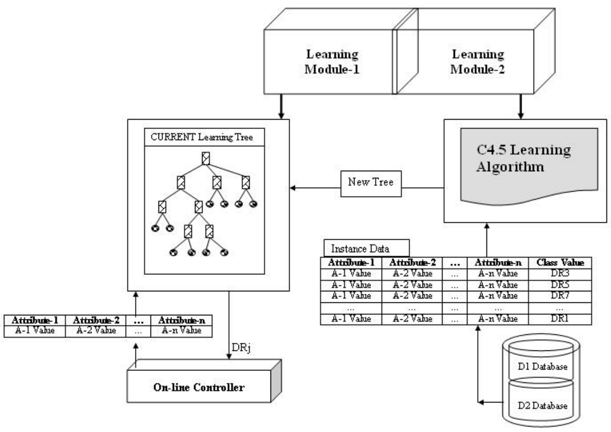


Figure 2: Learning Module

The scheduling strategy employed in this research is composed of two critical decisions: how-to-schedule and when-to-schedule. The How-to-schedule decision determines the way in which the schedules are revised or updated. As discussed in Sabuncuoglu and Goren (2003), there are mainly three issues: scheduling scheme, amount of data used, and type of the response. Our implementation is based on the "on-line" scheduling scheme. Specifically, DRs are selected by the learning tree and the scheduling decisions are made one at a time using these selected rules. In terms of the amount of data, we apply the "full" scheme, and as the type of response, we use the "reschedule" option, since a new DR is selected at any time when the performance of the existing DR in use is found to be poor.

"When-to-schedule" determines the responsiveness of the system to various kinds of disruptions. In this research a hybrid approach is employed for "when-to-schedule" decisions, in which two different triggering events, called *new rule selection symptoms*, are defined for determining the time of selecting a new DR. These new rule selection symptoms and their definitions are given in Table 1.

Table 1: New Rule Selection Symptoms

Abbreviation	Name	Description
BSP	Beginning of each Scheduling Period	Triggers the selection of a new DR at the beginning of each new scheduling period.
MP	Monitoring Points	Triggers the selection of a new DR at the monitoring points whenever necessary.

One of the distinguishing features of the proposed scheduling system is its mechanism that continuously updates the learning tree. This continuous update is important since the manufacturing system often undergoes various types of changes in time. In this context, the process control charts ($\overline{X}$ and R charts) act as a regulator of the learning tree. Moreover, the process control charts may also need to be updated due to changes in manufacturing conditions. Hence, as the proposed system evolves over time, two important decisions need to be made:

- Is it necessary to update the existing learning tree at current time *t*?
- Is it necessary to update the existing process control charts at current time *t*?

These two questions are to be answered every time when a new data point is plotted on the process control charts ($\overline{X}$ and R charts) and the decisions are made by the rules defined in the logical controller sub-module of the process controller module. These rules are defined in Tables 2 and 3 and are adapted from the literature (see, for example, DeVor et. al. 1992).

Table 2: Update Only Learning Tree Rules

Signal	Definition	Apply to
Extreme Points	$\overline{X}_i$ or R_i points that fall beyond the control limits of the $\overline{X}$ and R charts, respectively.	$\overline{X}$ and R charts
Zone-A signal	Two out of three $\overline{X}_i$ points in Zone-A (between 2σ and 3σ) or beyond.	$\overline{X}$ chart only
Zone-B signal	Four out of five $\overline{X}_i$ points in Zone-B (between σ and 2σ) or beyond.	$\overline{X}$ chart only

Table 3: Update Both Learning Tree and Process Control Charts Rules

Signal	Definition	Apply to
8 successive points	8 or more successive points strictly above or below the centerline	$\overline{X}$ and R charts
2 successive signals from Rule Set-1	Two successive occurrences of "Update Only Learning Tree Signals"	$\overline{X}$ and R charts

The learning module of the system generates a learning tree that relies on the manufacturing system characteristics. Decisions on selecting dispatching rules are given by the existing learning tree on-line. In such a system, the learning algorithm requires a number of attributes that can provide valuable information about the current manufacturing system conditions. These attributes, therefore, play a key role in the performance of the proposed system, since they impact the quality of the tree in the construction phase as well as in the decision phase (i.e., selection of the right DRs from the learning tree for a scheduling period). Hence, appropriate attributes are defined and used in such a way that they can represent a variety of important manufacturing system characteristics.

3 EXPERIMENTAL DESIGN AND COMPUTATIONAL RESULTS

3.1 Preliminary Analysis on System Parameters

In this section, we present the results of the experiments on the important system parameters, namely the scheduling period (SPL) and monitoring period lengths (MPL). SPL is a time interval during which a selected DR is used to schedule jobs. The rule can be changed before the end of the scheduling period if the performance of the system is found to be worse than a threshold value at the monitoring points. MPL is therefore defined to be the time interval between two successive monitoring points. In the following two sections, we present the results of the experiments on SPL and MPL, respectively. The simulation experiments are carried out under the following assumptions:

- The problem considered is a classical job shop problem with four machines given by Baker (1984).
- There is a set of candidate dispatching rules (CDR) that can be used (i.e., shortest processing time (SPT), modified due date (MDD), modified operation due date (MOD) and operation due date (ODD)).

When explaining the experimental results, we use three performance functions, called *Multi-pass Performance (MultiPass)*, *Best Performance (BestPerf)* and the *Learning Performance (LearnPerf)*. *MultiPass* is the average tardiness value achieved by the decisions of a multi-pass scheduling simulator. *BestPerf* is the minimum average tardiness value that can ever be achieved for a scheduling period, say period-j, by using any rule given in the candidate rule set. In other words, it is the best average tardiness value that we can achieve in period-j subject to the parameter values of the system, such as the scheduling and monitoring period lengths, the candidate dispatching rules and so on. We can calculate this value for a scheduling period-j only if the realization of random events during period-j is already known (i.e., we gather the scheduling period data of period-j). Finally, the learning performance in period-j, *LearnPerf*, is the realized average tardiness value of the rule selected by the learning tree. Note that, *BestPerf* gives a lower bound for the other two performance functions.

In the simulation experiments, two levels of utilization (i.e., low and high) and two levels of due date tightness (i.e., loose and tight) are considered. The two levels of utilization are taken to be 80% and 90%. Due dates are set by using the TWK due date assignment rule. The high and low levels are set in such a way that the percent of tardy (PT) jobs is approximately 10% and 40% under the FCFS rule for the loose and tight due date cases, respectively.

3.1.1 Simulation Results on SPL

As can be seen in Table 4, 11 different levels of scheduling period lengths are tested in the experiments for four due date and utilization level combinations. The simulation results are taken in steady state with 20 replications each with 200000 minutes of a planning horizon. To find *BestPerf*, scheduling rules are compared under the same experimental conditions using the common random number (CRN) scheme.

Table 4: Experimental Design of SPL

Factors	**Levels**
Scheduling period length	50, 100, 200, 500, 1000, 2000, 5000, 7500, 10000, 12500 and 15000

The result for the loose due date and 90% utilization case is depicted in Figure 3. Note that, results under 80% utilization case show the same behavior, as well. In this figure, single-pass performances of each dispatching rule are also displayed in addition to *BestPerf* and single-pass performance of SPT is found significantly worse than the other rules. The single-pass performances of MOD, ODD and MDD are almost equal. Also, *BestPerf* displays an exponential decay behavior as a function of SPL. It is interesting to note that for short scheduling period length selections, *BestPerf* is found to be significantly worse than the single-pass performances of the three dispatching rules (MOD, ODD and MDD). This is due to the fact that as SPL decreases, even though the selected rules seem to be the best for these short scheduling periods, the system switches to different rules so frequently that the performance of the system in the long run deteriorates. When we increase SPL, *BestPerf* begins to improve and converges to the single-pass performance of the rules MOD, ODD and MDD. Since the performances of the individual dispatching rules (MDD, ODD and MOD) are very close to each other in the long run for loose due-dates (as also stated by Baker 1984), switching between these rules doesn't provide any benefit. Therefore, *BestPerf* converges to a limit (single-pass performance of the rules) showing the behavior of an exponential decay function.

For the tight due dates, the experimental results show different behavior to some extent (see Figure 4-a and b). In Figure 4-a, single-pass performances of each dispatching rule are also displayed in addition to *BestPerf*. It is shown in the figure that the single-pass performances of the four dispatching rules are significantly different than each other and MOD performs at least twice better than the other rules. In addition, *BestPerf* displays an exponential decay behavior as we increase SPL, but having a minimum value at some point. For example in Figure 4, *BestPerf* reaches its minimum value at point A (i.e., SPL equals to 1000 minutes) and then it begins to deteriorate and converges to a limiting value when we further increase the scheduling

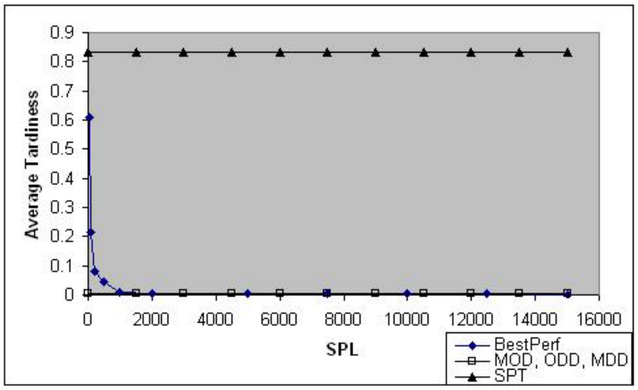
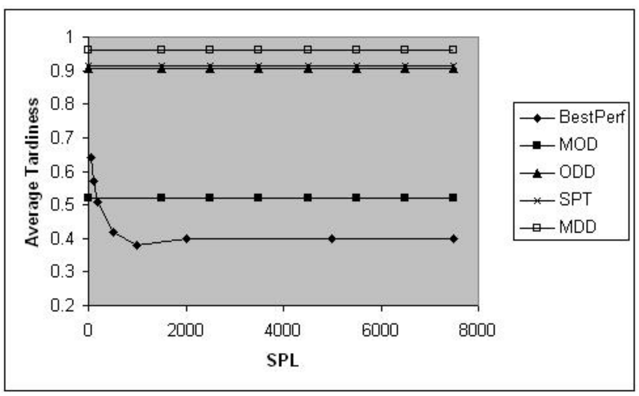
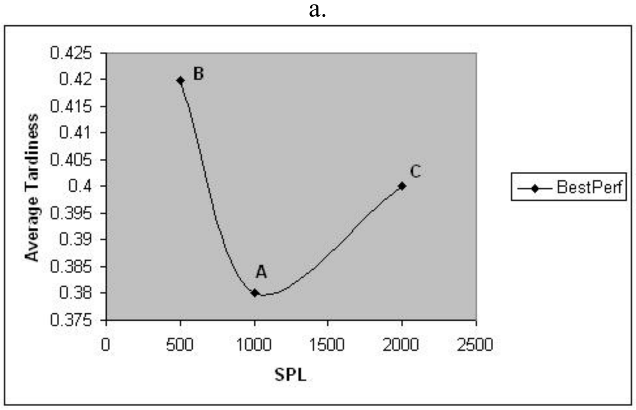


Figure 3: *BestPerf* under 90% Utilization and Loose Due-Dates



a.



b.

Figure 4: 80% Utilization, Tight Due-Dates: (a) Complete Display of the Results. (b) Zoom-In Version around Point A.

period length. We explain this interesting behavior as follows: choosing a shorter scheduling period length results in misdetection of the best dispatching rule for the sake of better long-run performance of the system (i.e., system switches between rules frequently). When we increase the scheduling period length, system begins to select the best rule combination and *BestPerf* reaches its minimum. But, when we continue to increase the scheduling period length further, performance deteriorates and converges to a higher value than the minimum. This higher value is close to the long-run performance of the most dominant dispatching rule, because the system begins to choose that rule most of the time. Thus, this significant increase in system performance is attributable to the loss of the improvements that can be achieved by switching to different rules during those long scheduling periods.

We also check whether the minimum points achieved in the tight due date case are statistically significant or not. Figure 4-b shows the magnified portion of Figure 4-a around the minimum point. We say that the point A is statistically smaller than the two neighboring points (i.e., points B and C) and this was verified by the paired-t test with 95% confidence.

3.1.2 Simulation Results on MPL

In this section we address the questions of how far the monitoring points should be apart from each other (i.e., the MPL) and what should be the value of the β-parameter, which is a parameter that defines the threshold value on the average tardiness measured at monitoring points. That is, if the average tardiness observed at any monitoring point is larger than β times the expected long run performance of the system ($\bar{\bar{X}}$), we select a new DR at that point in time.

A nested experimental design is given in Table 5, in which the factor monitoring period length (MPL) is nested inside the factor scheduling period length (SPL). Note that, MPL of 1000 for SPL being 1000 corresponds to the case of no monitoring at all, since they are equal. 12 levels of the β parameter are used in the experiments. The value of $\bar{\bar{X}}$ is taken to be 0.6795 and 1.195 for 80% and 90% utilizations, respectively. These values are the *BestPerf* values for 80% and 90% utilizations with respective SPLs (i.e., SPL=1000 for 80%, SPL=7500 for 90% utilization), which we found in the previous section.

Table 5: Experimental Design of MPL and β-Parameter

Factors	Levels						
Due-date tightness	Tight						
β	0.2, 0.5, 0.8, 1, 1.4, 1.8, 2.2, 2.4, 2.6						
Utilization	80%			90%			
SPL	1000			7500			
MPL	250	500	1000	500	2500	3750	7500

As a summary of our results, we found that for both 80% and 90% utilizations, monitoring the system performance at discrete points in time improves our objective function (i.e., average tardiness). Also, experiments show that it is vitally important to select not only the right monitoring period length, but also the right β parameter for that MPL. For example, for the 90% utilization case, a MPL of 2500 with a β value other than 1 results in worse performance measures than no monitoring case (i.e., mean tardiness values greater than 1.195). Moreover, for both 80% and 90% utilizations, system performance improves with small monitoring period lengths. In addition to that, for small monitoring period lengths, small β values work better. For example, for 80% utilization, it is best to choose β=0.2 when MPL=250 whereas β=1 when MPL=500.

3.2 Performance of Learning-Based System

In this section, we test our system with a dynamic learning tree (i.e., all of its modules discussed in Section 2 are activated). In other words, we now continuously monitor the quality of the learning tree by the control charts and update it whenever necessary. Thus, we call this experiment scheduling with a *dynamic learning structure*.

In the simulation experiments, we consider a manufacturing system in which its internal parameters change in time (i.e., arrival rate, due date tightness levels). The details of the experimental design are given in Table 6. Note that, we use 5 planning horizons, where each horizon contains 1000 scheduling periods. At the beginning of each horizon, we change some of the parameters of the manufacturing system. For example, in Table 6, the factor "parameter sequence for arrival rate" represents the value of the arrival rate of the jobs during each horizon. Specifically, in horizons 1, 2, 3, 4 and 5, jobs arrive exponentially with parameters 0.8, 0.9, 0.7, 0.9 and 0.8, respectively. For the construction of the learning tree, we consider two different strategies, which are represented by the factor "Training Data Set" in Table 6. When this factor is at its level Full, the learning tree is constructed based on all the accumulated data points since the beginning of the experiment. On the other hand, if its level is set to Partial, the most recent 200 data points (1/5 of a horizon length) are used each time when the learning tree is updated.

We consider three levels for the SM2 type: *reactive*, *non-reactive* and *partially reactive*. When SM2 type is reactive, the multi-pass simulation model is updated immediately when there is any parameter change in the actual manufacturing environment. In other words, if the arrival rate of the jobs changes in real world, this information is made available for the multi-pass simulation model immediately. Intuitively, this is impossible in real world implementation, because when any parameter of the manufacturing system changes it can be made available to the simulation model of the system after a period of time. This delay is inevitable since detecting the shift in the parameters requires data collection and statistical analysis. For this reason, we also consider the partially reactive level for SM2 type. When the type is partially reactive, the multi-pass simulation model is updated for the arrival rate changes, but with some time delay and an accuracy level. Specifically, arrival rate is updated with a delay of 200 scheduling periods (1/5 of a horizon length) after the actual change in the real world takes place and set to the values in the sequence {0.8, 0.875, 0.725, 0.875, 0.8} for each horizon 1 through 5, respectively. The time delay for the update represents the passage of time for collecting sufficient data, which is necessary to statistically determine the new arrival rate. As another extreme, we consider SM2 type as non-reactive. In this case the model is not updated for any changes in the manufacturing environment. For example, when the arrival rate changes from 0.8 to 0.9 in the real world, the multi-pass simulation model continues to operate under the initial arrival rate, which is 0.8.

Table 6: Experimental Design for Scheduling with Dynamic Learning Structure

Factors	Levels
DR set	{MOD, MDD, ODD, SPT}, {MDD, ODD, SPT}
Sequence for arrival rate parameter	{0.8, 0.9, 0.7, 0.9, 0.8}
Horizon lengths (number of SPs)	1000
Training Data Set	Full, Partial (1/5 of horizon length)
SM2 type	Reactive, non-reactive, partially reactive
Due date tightness	Adjusted, not adjusted
(SPL, MPL, β)	{(1000, 250, 0.2), (7500, 500, 0.2)}

Another factor considered in the experiments is *due date tightness* and it has two levels, *adjusted* and *not adjusted*. For the adjusted case, we set the allowance factor k for setting the due dates such that the percent tardy is always 40% under the FCFS rule. For the not adjusted case, the flow allowance factor is always at the level 5.5 for all arrival rates. Therefore, the first case corresponds to a policy such that the manufacturing firm adjusts its due date setting policy when the arrival rate of the jobs changes and in the second case no action is taken for setting the due dates of the jobs when the utilization of the shop floor changes.

The last factor that we consider in the experiments is the choice of scheduling and monitoring period lengths along with the β value. For the levels of this factor, we simply consider the best combinations that we previously determined for 80% and 90% utilization levels. Therefore, the two levels, (1000, 250, 0.2) and (7500, 500, 0.2), are considered for this factor. At the beginning of each experiment, there is a warm up period with a length of 200 scheduling periods to provide necessary initial data to the system to construct the first learning tree and the control charts. System statistics are initialized after the warm up

Table 7: Average Tardiness Values of the Experiments for DR Set {MDD, ODD, SPT}

		Training data set:	**Full**		**Partial**	
		(SPL, MPL, β)	**(1000, 250, 0.2)**	**(7500, 500, 0.2)**	**(1000, 250, 0.2)**	**(7500, 500, 0.2)**
Due date tightness:	**SM2 type:**					
Adjusted	**Reactive**	MultiPass	1.18	1.25	1.18	1.25
		LearnPerf	1.1	1.11	1.13	1.2
		BestPerf	0.98	1.02	0.98	1.02
	Non-reactive	MultiPass	1.37	1.52	1.37	1.52
		LearnPerf	1.1	1.11	1.13	1.2
		BestPerf	0.98	1.02	0.98	1.02
	Partially Reactive	MultiPass	1.25	1.32	1.25	1.32
		LearnPerf	1.1	1.11	1.13	1.20
		BestPerf	0.98	1.02	0.98	1.02
Not Adjusted	**Reactive**	MultiPass	2.38	1.79	2.38	1.79
		LearnPerf	2.3	1.75	2.42	1.9
		BestPerf	2.15	1.71	2.15	1.71
	Non-reactive	MultiPass	2.59	2.26	2.59	2.26
		LearnPerf	2.3	1.75	2.42	1.9
		BestPerf	2.15	1.71	2.15	1.71
	Partially Reactive	MultiPass	2.49	2.02	2.49	2.02
		LearnPerf	2.3	1.75	2.42	1.9
		BestPerf	2.15	1.71	2.15	1.71

Table 8: Average Tardiness Values of the Eexperiments for DR Set {MDD, ODD, SPT, MOD}

		Training data set:	**Full**		**Partial**	
		(SPL, MPL, β)	**(1000, 250, 0.2)**	**(7500, 500, 0.2)**	**(1000, 250, 0.2)**	**(7500, 500, 0.2)**
Due date tightness:	**SM2 type:**					
Adjusted	**Reactive**	MultiPass	0.81	0.65	0.81	0.65
		LearnPerf	0.81	0.65	0.82	0.68
		BestPerf	0.71	0.6	0.71	0.6
	Nonreactive	MultiPass	0.96	0.73	0.96	0.73
		LearnPerf	0.81	0.65	0.82	0.68
		BestPerf	0.71	0.6	0.71	0.6
	Partially Reactive	MultiPass	0.87	0.69	0.87	0.69
		LearnPerf	0.81	0.65	0.82	0.68
		BestPerf	0.71	0.6	0.71	0.6
Not Adjusted	**Reactive**	MultiPass	1.52	1.2	1.52	1.2
		LearnPerf	1.2	1.15	1.61	1.27
		BestPerf	1.15	1.1	1.15	1.1
	Nonreactive	MultiPass	1.67	1.35	1.67	1.35
		LearnPerf	1.2	1.15	1.61	1.27
		BestPerf	1.15	1.1	1.15	1.1
	Partially Reactive	MultiPass	1.6	1.26	1.6	1.26
		LearnPerf	1.2	1.15	1.61	1.27
		BestPerf	1.15	1.1	1.15	1.1

period and each experimental condition is run for 5 consecutive horizons (5000 scheduling periods) as it is given in Table 6. The results of the experiments, *MultiPass*, *LearnPerf* and *BestPerf*, are summarized in Tables 7 and 8. Note that, *BestPerf* provides the lower bound values for both *MultiPass* and the *LearnPerf*.

From these results, our first observation is that our learning-based scheduling system outperforms the simulation-based scheduling approach (*MultiPass*) in 38 experimental conditions out of 48. In these cases, *LearnPerf* is closer to *BestPerf* more than *MultiPass* in a range of 2.34% to 40.87%. In 2 cases, both *MultiPass* and *LearnPerf* are found to be equal. In the remaining 8 cases simulation-based scheduling (*MultiPass*) performs slightly better than *LearnPerf* (i.e., between 1.68% and 7.83% better). However, in these cases SM2 type is reactive, which is a difficult condition to achieve in the real world.

When we compare *LearnPerf* for full and partial training data set cases, we see that using all available data always results in better performance (see Tables 7 and 8). At first glance, this seems to be counter intuitive because when parameters of the manufacturing system change, learning with the most recent data is expected to yield better performance. However, the results show that our learning algorithm gets benefit from the past data as well as the recent data.

The third observation is related with the selection of SPL, MPL and β values. For the rule set of {MOD, MDD, ODD, SPT}, the combination (7500, 500, 0.2) always gives better results for *LearnPerf* than the combination (1000, 250, 0.2) (Table 8) regardless of partial or full data sets being used. The reason why the combination (7500, 500, 0.2) yields better results when MOD is in the rule set is that the performance of MOD dominates the performance of other rules when it is used for a long period of time. Thus, the combination (7500, 500, 0.2) yields better results than the combination (1000, 250, 0.2). For the rule set {MDD, ODD, SPT}, the best choice of (SPL, MPL, β) combination depends on the parameter “due date tightness”. When the due date tightness factor is at its level *not adjusted*, the choices of (7500, 500, 0.2) results again in better performance than (1000, 250, 0.2) regardless of the partial or full data sets being used. But, when it is at the *adjusted* level, (7500, 500, 0.2) and (1000, 250, 0.2) result in better performance for the full and partial training data sets, respectively, (Table 7). These results stress the importance of the appropriate selection of SPL, MPL and β values once more.

As stated before, partially reactive SM2 is a more realistic case where the simulation model used for the scheduling decisions of multi-pass approach is updated with some time delay and inaccuracy that may exist in detecting the parameter changes in the actual manufacturing environment. Therefore, the comparison of the learning-based (*LearnPerf*) and the simulation-based (*MultiPass*) systems for this factor level is of special importance. When the SM2 type is partially reactive, *LearnPerf* is better than *MultiPass* in 14 cases out of 16. That is, *LearnPerf* is closer to *BestPerf* more than *MultiPass* in a range of 3.26% to 34.79% in these 14 cases. In the remaining 2 cases, *MultiPass* is closer to *BestPerf* more than *LearnPerf* only 0.9%, which means they are almost equal.

4 CONCLUSION

In this paper, we present a learning-based scheduling system for a classical job shop problem with the average tardiness objective. We perform extensive simulation experiments. The results indicate that it is very important to select the appropriate values for SPL, MPL and β. For poorly selected parameters, performance of multi-pass methods can be worse than the single-pass performances of the individual dispatching rules. The results also indicate that the proposed system performs better than the simulation-based multi-pass scheduling and the single-pass scheduling. But for very large values of monitoring intervals, the performance of the proposed system deteriorates to the level of the performance of the multi-pass scheduling system. Hence, at this point we conclude that the monitoring process is really essential for our learning based algorithm. Moreover, when we add a competitive dispatching rule (i.e., MOD) to our rule set, the performance of the proposed system as well as the *MultiPass* further improves (gets closer to *BestPerf*). Hence, deciding the rules in the candidate dispatching rule set is also important for the performance of our learning algorithm.

REFERENCES

Cho, H., and Wysk, R.A. 1993. A robust adaptive scheduler for an intelligent workstation controller. *International Journal of Production Research* 31 (4): 771-789.

DeVor, R. E., Chang, T-h., and Sutherland, J. W. 1992. *Statistical Quality Design and Control*. New Jersey: Prentice Hall.

Ishii, N., and Talavage, J.J. 1991. A transient-based real-time scheduling algorithm in FMS. *International Journal of Production Research* 29 (12): 2501-2520.

Jeong, K. –C., and Kim, Y.-D. 1998. A real-time scheduling mechanism for a flexile manufacturing system: using simulation and dispatching rules. *International Journal of Production Research* 36: 2609-2626.

Kutanoglu, E., and Sabuncuoglu, I. 2001. Experimental investigation of iterative simulation-based scheduling in a dynamic and stochastic job shop. *Journal of Manufacturing Systems* 20: 264-279.

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

Quinlan, J.R. 1993. *C4.5 Programs for Machine Learning*, California: Morgan Kaufmann.

Sabuncuoglu, I., and Goren, S. 2003. A review of reactive scheduling research: proactive scheduling and new robustness and stability measures. Technical working paper, Department of Industrial Engineering, Bilkent University.

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

Suwa, H., and Fujii, S. 2003. Rule acquisition for rolling horizon heuristics in single machine dynamic scheduling. *Proceedings of the 7th World Multiconference on Systemics, Cybernetics and Informatics* 13: 279-284.

Tayanithi, P., Minivannan, S., and Banks, J. 1993. A knowledge-based simulation architecture to analyze interruptions in a flexible manufacturing system. *Journal of Manufacturing Systems* 11 (3): 195-214.

Wu, S.D., and Wysk, R.A. 1988. Multi-pass expert control system – a control/scheduling structure for flexible manufacturing cells. *Journal of Manufacturing Systems* 7 (2): 107-120.

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